Essays in Numerical Finance

Dissertation
submitted to the
Faculty of Business, Economics and Informatics
of the University of Zurich

to obtain the degree of
Doktor der Wirtschaftswissenschaften, Dr. oec.
(corresponds to Doctor of Philosophy, PhD)

presented by

Andreas Thomann
from Basel, Basel-Stadt

approved in April 2019 at the request of

Prof. Dr. Karl Schmedders
Prof. Dr. Ole Wilms

The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

Zurich, 03.04.2019

Chairman of the Doctoral Board: Prof. Dr. Steven Ongena

Acknowledgements

My PhD studies would not have been possible without the support of so many amazing people in my life. First and foremost, my advisor, Karl Schmedders, gave me the opportunity to pursue my PhD studies and played a huge role throughout this project. His continued support over the years, his awareness of and sympathy for my situation as an external PhD student, paired with his motivational and energizing personality helped me a great deal in cushioning and overcoming the hard times during my studies. Also, I would like to thank Ole Wilms for acting as co-advisor in my thesis committee. Furthermore, I would like to thank my project partners, Andrea Laurent, formerly—and during my first two projects—with Union Bancaire Privée, and Lorenz Beyeler and Cyril Bachelard from the research department of OLZ AG, for rewarding discussions. Moreover, I am incredibly thankful for the limitless support—in every aspect of life—of my friends Jean-Michel Benkert, Philipp Braun, Benjamin Saladin, and Timo Tondelli.

As with everything, I could not have done this without my family. I thank my parents Jean-Paul and Verena, my sister Simone, and my brother-in-law, Jan.

Andreas Albert Thomann, Zurich, December 2018

Contents

Part I

Dissertation Overview

Dissertation Overview

This dissertation consists of three separate chapters, all of which are related to numerical finance. While the first two chapters focus on applications of price simulations, the third chapter is related to the field of numerical finance as I present a systematic, data-based approach to supporting investment management decisions regarding sovereign bonds. In what follows, I give a brief outline of each chapter and try to highlight the connections between them.

In Chapter 1, I tackle the inherent problem of trend-following investment strategies, which is their lagging trading signals. As Murphy (1999, p. 197) states for the moving average cross—a special type of trend-following investment strategy: It "does not [...] predict market action. [...] [It] is a follower, not a leader. It never anticipates; it only reacts. The moving average follows a market and tells us that a trend has begun, but only after the fact." As this regularity typically leads to sharp drawdowns, I apply a semi-parametric scenario building approach based on the methodology laid out in Barone Adesi et al. (1999) to circumvent this disadvantage. To do so, I extract information contained in the observed price and volatility to jointly simulate both and, thereby, generate artificial price and volatility paths. I show that using this approach to build the trading signals for trend-following strategies improves the risk-return properties of the strategy relative to both the passive buy-and-hold strategy and the standard moving average cross strategy.

In Chapter 2, I present a new backtesting framework for numerical investment strategies. In contrast to traditional ways of backtesting trading strategies, the presented environment allows for robustness checks on artificially created price paths that experience similar statistical properties as the observed price series. Current research, including Bailey et al. (2017), Harvey et al. (2016), and Harvey and Liu (2015), criticizes methods and results from empirical studies that document statistically significant results. My framework is not affected by these findings as I merely provide a tool for robustness checks rather than an optimization engine. Therefore, my framework extends the abovementioned research in that it allows the trader to put his or her strategy to the test by stress testing his or her own results. I therefore rather align myself with the aforementioned current research as I too propose that backtesting results be challenged with rigor. The model underlying this framework is based on Barone Adesi et al. (1999) and does not need prior specification of distributional features. By backtesting a number of technical indicators based on standard calibrations, I show how performance measures such as the Sharpe ratio, excess return, maximum drawdown, but also the statistical moments of the return distribution, are influenced.

In Chapter 3, I present a study in which I develop a bond market factor strategy to manage interest rate risk for sovereign bond investments in the Swiss market and globally. The presented model is based on a combination of macroeconomic and style factors as these have distinct features and therefore are expected to behave differently, thereby improving the quality of the generated investment signal. The bond market factor is a combination of four individual factors. While the input factors are no novelty and are documented in financial research, I show that an algorithm for transforming the data into a signal-generating model helps improve investment decisions significantly, enhancing a wide range of performance metrics relative to the passive buy-and-hold strategy.

As has hopefully become clear, all three chapters deal with the design and implementation of investment decision models and with the question of how active investment management effectively influences investment performance, and how this performance can be improved. While the presented studies are highly specific and applied in their nature, they are mostly relevant to investment professionals and academics working in the areas of investment strategies and portfolio management, but also to the general public, as almost every individual is faced with investment decisions—whether it be consciously or unconsciously. With this in mind, I invite you to continue reading and learn more about numerical investment strategies and portfolio management.

Part II

Research Papers

1 Multi-asset Scenario Building for Trend-Following Trading Strategies[1]

1.1 Introduction

The price evolution of a financial asset is just one realization of a stochastic process that is one out of many possible histories. It is therefore interesting to build alternative price paths of financial assets in order to build more robust trading strategies. In particular, this paper uses a distribution-agnostic scenario building process that does not require a prior definition of the probability distribution of the return process. The scenario building process empirically explored in this paper is based on Barone Adesi et al. (1999), a process that they call filtered historical simulation. It combines the empirical distribution of past returns and nonlinear econometric models to simulate possible future values of an asset in the days ahead. From a statistical perspective it is a semi-parametric model. We use this approach, which has emerged from financial risk management, adapt it to our needs, and apply it to trading strategies. Using the empirical distribution of past returns implies that the price series does not have to conform to a theoretical probability distribution. Other well-known simulation models, such as the Monte Carlo method, draw innovations from predetermined theoretical distributions, thereby smoothing the empirical distribution and, also, introducing errors that might lead to the underestimation of the probability of certain scenarios due to a lack of implied skewness and kurtosis in the assumed distribution. From a computational perspective, the parallel bootstrapping process implicitly handles the cross dependencies among the data series. Our simulation process therefore reduces the complexity of the task enormously as the number of parameters and the time needed to execute the computation increase only linearly with the number of assets that are handled (see Barone Adesi et al. (1999)). This is different to approaches that model cross dependencies based on estimates of the variance–covariance matrix, where the dimension of the problem increases quadratically with the number of assets. The artificial price paths generated by the scenario building process are used to improve trend-following trading strategies based on moving average cross systems, known from the field of technical analysis (e.g., Murphy (1999)). Moving average cross systems are widely applied in the financial industry (see for example Man Group's working paper by Granger et al. (2014) or AQR Capital Management's working paper by Hurst et al. (2014)) and are found to be a good instrument for market timing (see Marshall et al. (2014)).
This paper is organized as follows: We start our paper with the most important empirical findings on asset price and volatility behavior, in Section 1.2. Using these findings as a starting point allows a smooth transition to Section 1.3, where we discuss the history and evolution of asset price simulation from a financial risk management perspective. We continue with a theoretical

[1]This paper should be cited as Thomann, A. (2018), "Multi-asset Scenario Building for Trend-Following Trading Strategies". A modified version of this paper has been submitted to the *Annals of Operations Research*.

part in Section 1.4 where we explain the scenario building process applied in this paper. In two subsections we provide details and explain the methodology used in this paper for simulating asset prices and volatility. Section 1.5 focuses on the tested trading strategies. Subsection 1.5.1 explains our trend-following benchmark strategy that we are trying to outperform in this paper in terms of Sharpe ratio and maximum drawdown. To do so, we start with the very basics and explain the idea behind the moving average cross strategy and its characteristics. The following subsection, 1.5.2, covers our first optimized trading strategy, named “median simulated price strategy”, and explains its construction. Then, we review the construction of the “probability strategy”—our second optimized trading strategy—in Subsection 1.5.3. Section 1.6 explains our way of evaluating performance and also represents the last theoretical part. Section 1.7 contains all the empirical results of our study. We start with a description of our tested dataset, before providing an overview of our model parametrization for our baseline results in Subsection 1.7.1. The subsequent Section, 1.7.2, provides an insight into our simulated price series. In Subsections 1.7.3 and 1.7.4 we comment our main empirical results. We challenge our empirical findings in various robustness checks, which are available in our “Appendix to Multi-asset Scenario Building for Trend-Following Trading Strategies”.[2] Section 1.9 concludes this paper with a final review of our main findings and a short summary.

1.2 Volatility and Return Modeling

Before going into details about the scenario building process used in this paper, we review the fundamental empirical findings on volatility to get a good understanding of how to possibly model it. Mandelbrot (1963) and Black (1976) have each authored well-known papers that describe the characteristics of asset return volatility. They document the existence of volatility clusters, which means that high/low volatility is often followed by high/low volatility. Another finding is that volatility evolves over time—that is to say, jumps in asset return volatility are seldom observed. The concept of volatility stationarity states that volatility stays within a range and does not diverge to infinity. The leverage effect in volatility is another mentionable finding, stating that volatility reacts differently to increases and decreases in the price of an asset. These findings are important in the volatility modeling process and therefore also when simulating price paths using a scenario building process.

1.3 Scenario Building Models

Our scenario building process evolved from historical simulation using a bootstrapping algorithm. To appreciate the process and understand its advantages we first give an overview of the most important and widely used scenario building models in the financial industry and academia. Scenario building models are relied on heavily in financial risk management, where, for example, RiskMetrics—a model based on the variance-covariance of historical realized returns, has been used for years (see Zangari (1996) or Mina and Xiao (2001)) and is still taught in academia. The original model assumes that the data follows a theoretical, often a Gaussian, distribution

[2]Online appendix.

with constant mean and variance. This linear Value-at-Risk model therefore imposes strong assumptions about the underlying data, which are confuted or at least challenged by the empirical findings of financial research (see for example Kendall (1953) or Mandelbrot (1963)). One can also observe that asset prices can move much more strongly in each direction than a Gaussian distribution predicts. As a possible solution, Embrechts et al. (1997) and Longin (2000) suggest using the extreme value approach, which helps solve the problem of underestimating outliers in the distribution but has other short-comings. To circumvent the drawbacks of the linear models described above, academics and practitioners moved to simulations to assess the risk of a portfolio. A well-established model is the Monte Carlo simulation, which is based on random numbers drawn from a theoretical distribution function. As with the linear model, the Monte Carlo method usually relies on a Gaussian distribution. This yields to the same problems as above: using a distribution function that does not fit the empirical distribution of most assets and therefore also limiting the moves of asset prices in each direction. This means that gains and losses are limited to around three to four standard deviations using a large enough set of simulations (see Barone Adesi et al. (2002)). Additionally, in a multi-asset context the Monte Carlo method is based on historical correlations between the assets. In times of market stress however, the correlations between assets typically move toward one, which leads the Monte Carlo method to possibly underestimate losses. To circumvent this problem, the variance–covariance matrix can be estimated more frequently, which increases the computational effort needed in an already computationally intense algorithm. Identifying the problem that asset returns cannot be properly described using a theoretical, especially not a Gaussian, distribution, the industry has moved to historical simulation, which is based on observed historical price changes. This approach also has its drawbacks: The rationale behind using historical returns instead of using a theoretical distribution is that we also want to consider extreme events, which are not properly captured in most theoretical distributions. This, however, requires using long time series data to ensure our data sample contains these extreme events we want to include in our simulation. Additionally, and more severe, the approach does not take into account the fact that asset risks can evolve over time. Together with the implied assumptions of independent and identically distributed returns the risk might be underestimated (see for example Vlaar and Palm (1993) or Vlaar (2000)). Barone Adesi et al. (1998) and Barone Adesi et al. (1999) tackle these problems and present a model called “filtered historical simulation”. They suggest randomly picking standardized returns from historical returns. Afterward, standardized returns need to be scaled by the current volatility the asset experiences if they are to be used as innovations in a conditional variance equation for the scenario building process that models both the future price of an asset as well as its variance. This approach allows a simulation of the entire distribution of asset returns, taking into account the weaknesses of other models explained above, such as changes in volatility. Filtered historical simulation is the basis of our scenario building process and we discuss it in more detail in the next section.

1.4 Scenario Building Process

Filtered historical simulation has been developed to avoid the drawbacks accompanying underlying historical simulation—its reliance on a specific distribution as well as the fact that it does not take into account empirical findings such as the existence of volatility clustering, fat tails, and the leverage effect (see Mandelbrot (1963) and Black (1976)). Its usage of past return indicates that the presented model originates from historical simulation. This historical return data is used as innovations to model the behavior of asset prices. Compared to historical simulation, its major enhancement is that the return is first adjusted by the volatility that was observed at that day and—in a second step—is multiplied by the forecasted volatility. This adjustment guarantees, that the past returns are stationary such that they are suitable innovations for the simulation process (see for example Posedel (2005) for a derivation of stationarity). The rescaling with volatility forecasts introduces the current market conditions to the past returns. The process described here in few words is explained in more detail and in a more formal way below.

Summarizing the benefits of using the approach of Barone Adesi et al. (1999), the most important point to emphasize is the fact that the data is not forced to originate from a theoretical, pre-specified distribution. Fat tails, volatility clusters, and changing means are all peculiarities that are allowed in this model—as it is based on the empirical distribution. We therefore take most of the empirical volatility modeling findings into account when building our artificial price and volatility paths. The model is able to handle dependencies across a very large set of assets without estimating the correlation matrix, and therefore has interesting properties from a computational perspective. It is possible to build scenarios in which simulated asset prices result from large returns following other large returns. We interpret such a scenario as an extreme scenario that might possibly not be included in the raw data as such. On the other hand, even though we break up existing autocorrelation, this scenario building process allows the generation of new trends that our trading strategies try to exploit. We see this as an additional advantage compared to historical simulation as this also moderates the requirements with respect to our dataset to include every possible scenario. To demonstrate how the scenario building process works, we follow the example of Barone Adesi et al. (1999) and first explain the simulation of a single pathway and afterwards of multiple pathways.

1.4.1 Scenario Building for a Single Pathway

Simulating a single pathway for one asset is less complicated and therefore helps us to understand the underlying methodology and how it is applied to data. The two most important variables we have to specify in the scenario building process are the number of simulation runs we want to perform (the number of artificial price paths we want to simulate) and the number of days (or whatever data frequency we are using) we want to simulate prices into the future. In our baseline model we chose the number of simulations to be 200 and we simulate the price path 10 days ahead. We will address the days-ahead issue in the robustness checks in the additional appendix to this paper in more detail and provide insights into how to specify this parameter. We fit a GARCH model based on an initial data sample, which in our case is specified to be at least 100 daily observations. Estimating the GARCH model forms residual returns from the raw return data. By filtering these residual returns they turn independent and identically distributed, and, thereby, become applicable for the scenario building process. Our algorithm therefore also removes serial correlation and volatility clusters if the data contains such structures. Barone Adesi et al. (1999) call their approach semi-parametric since it combines non-

parametric historical simulation together with the parametric GARCH model. The standard model used in Barone Adesi et al. (1999) and demonstrated here as our baseline model is the GARCH(1,1) model. Using their notation, with a moving average term, θ, and an autoregressive term, μ, our estimates of the residuals, ϵ_t, and the variance, h_t, are defined as below.
The conditional mean equation can be written as follows:

$$r_t = \mu r_{t-1} + \theta\epsilon_{t-1} + \epsilon_t \qquad \epsilon \sim \mathcal{N}(0, h_t). \tag{1.1}$$

The conditional variance equation can be written as follows:

$$h_t = \omega + \alpha(\epsilon_{t-1} - \gamma)^2 + \beta h_{t-1}. \tag{1.2}$$

The GARCH equation (1.2) specifies the volatility of ϵ_t as a function of ω, a constant, a first term demonstrating the contribution of the latest surprise, ϵ_{t-1}, and a second term reflecting the contribution of the last period's volatility, h_{t-1}. α is a constant and determines the influence of the most recent observation whereas the constant γ determines its asymmetry. We divide the estimated residuals, $\hat{\epsilon_t}$, by the corresponding volatility estimate, $\sqrt{\hat{h_t}}$, to get a stationary i.i.d. distribution, which is suitable for our simulation process,

$$e_t^* = \frac{\hat{\epsilon_t}}{\sqrt{\hat{h_t}}}. \tag{1.3}$$

If the GARCH model is correctly specified the set of standardized residuals, e_t^*, is independent and identically distributed and therefore suitable for historical simulation.[3] This is in contrast to empirical returns, which generally do not fulfill the i.i.d. assumption and therefore are unsuitable for historical simulation.

Randomly drawn historical standardized residuals need to be scaled with the current volatility. Afterward, they can be used in the equations for the conditional mean (1.1) and variance (1.2) to simulate future prices and variances. This random draw is better known as resampling or bootstrapping, which is what filtered historical simulation essentially does. Randomly, we pick standardized residual returns and use them to generate a pathway of variances that themselves are used to build our alternative price path. The randomly drawn standardized residual returns are stored as a vector, $\boldsymbol{e}^*$, of outcomes.

$$\boldsymbol{e}^* = \{e_1^*, e_2^*, \ldots, e_T^*\} \qquad \text{where i} = 1, \ldots, T \text{ days.} \tag{1.4}$$

We use the first drawn standardized residual return and scale it using the deterministic volatility forecast for the next day. The deterministic volatility for the next day is constructed as

$$h_{t+1} = \hat{\omega} + \hat{\alpha}(\epsilon_t - \hat{\gamma})^2 + \hat{\beta} h_t. \tag{1.5}$$

The simulated innovation forecast is created by scaling the randomly drawn standardized resid-

[3] We provide the empirical test results on the i.i.d. properties, where we use the test of Li and Mak (1994) on the squared residual autocorrelations in nonlinear time series with conditional heteroscedasticity, upon request and publish them in our online appendix.

ual, e_t^*, with the volatility of period $t+1$, h_{t+1}, from Equation (1.5).

$$z_{t+1}^* = e_1^* \sqrt{h_{t+1}}. \tag{1.6}$$

This simulated innovation forecast is used to shape the one-day-ahead asset price forecast, p_{t+1}^*, using the asset price at time t, p_t:

$$p_{t+1}^* = p_t + p_t(\hat{\mu} r_t + \hat{\theta} z_t^* + z_{t+1}^*). \tag{1.7}$$

To forecast the volatility for subsequent days ahead we simulate them by recursively substituting the scaled residuals into the variance equation (1.2). Therefore, our first randomly drawn standardized residual from Equation (1.3) enters into the one-day-ahead asset price forecast from Equation (1.7), but is also used for the simulation of the two days ahead volatility forecast. The two-days-ahead volatility is stochastic as it depends on the simulated return of the first day. To simulate the two-days-ahead asset price we randomly pick another standardized residual and scale it. The volatility three days ahead is generated using the previously drawn (second) scaled residual and allows the scaling of the third randomly drawn residual et cetera up until we reach the number of asset price simulations we want to achieve. The volatility simulation takes the following general form:

$$h_{t+i}^* = \hat{\omega} + \hat{\alpha}(z_{t+i-1}^* - \hat{\gamma})^2 + \hat{\beta} h_{t+i-1}^* \qquad i \geq 2. \tag{1.8}$$

The process allows the sequential scaling of randomly drawn standardized residuals to build the asset price pathway. Repeating this process allows us to form various pathways of asset prices. We discuss the underlying methodology for doing so in the following section.

1.4.2 Scenario Building for Multiple Pathways

To simulate multiple pathways, we use the same approach as explained in the previous section. One of the most important aspects when simulating multiple pathways for different assets is how to model the correlation between the assets. In our scenario building process this is done implicitly by randomly drawing a band of residuals as we use the same standardized residual from the same observation for the price and volatility simulation of each asset. We therefore do not need to estimate the correlation matrix. In our multi-asset framework we randomly draw a date from the dataset and pick its corresponding residual returns. These residual returns are used to model the co-movements between the prices of our multi-asset dataset. For each asset in our dataset we have the sampled residuals and denote them with subscripts $1, 2, 3, \ldots, n$ for the different assets. In our case, the number of tested assets is equal to two, since we report the backtesting results of the MSCI World and S&P 500 Index.

$$Asset_1 : \boldsymbol{e_1^*} = \{e_1^*, e_2^*, \ldots, e_T^*\}_1. \tag{1.9}$$

$$Asset_2 : \boldsymbol{e_2^*} = \{e_1^*, e_2^*, \ldots, e_T^*\}_2. \tag{1.10}$$

As in the case for the single pathway, we draw a random date and the associated standardized residuals at day $i = 1$, e_1^* and e_2^* are chosen. At day $i = 2$ another date is randomly drawn together with its associated standardized residuals. This is repeated until we have reached our specified number of daily asset price forecasts. For every asset, the variances, h, and asset prices, p, are modeled such that they reflect the co-movements between each other. For every day $i = 1$ to T we therefore have

$$Asset_1 : h_{1,t+i}^* = \hat{\omega}_1 + \hat{\alpha}_1(\hat{z}_{1,t+i-1}^* - \hat{\gamma})^2 + \hat{\beta}_1 h_{1,t+i-1}^*. \tag{1.11}$$

$$p_{1,t+i}^* = p_{1,t+i-1} + p_{1,t+i-1}(\hat{\mu}_1 r_{1,t+i-1} + \hat{\theta}_1 z_{1,t+i-1}^* + z_{1,t+i}^*). \tag{1.12}$$

$$Asset_2 : h_{2,t+i}^* = \hat{\omega}_2 + \hat{\alpha}_2(\hat{z}_{2,t+i-1}^* - \hat{\gamma})^2 + \hat{\beta}_2 h_{2,t+i-1}^*. \tag{1.13}$$

$$p_{2,t+i}^* = p_{2,t+i-1} + p_{2,t+i-1}(\hat{\mu}_2 r_{2,t+i-1} + \hat{\theta}_2 z_{2,t+i-1}^* + z_{2,t+i}^*). \tag{1.14}$$

We extend the original methodology for the scenario building process for multiple pathways in terms of price and volatility path modeling: we adjust the price modeling process such that at day t we use the observed price to model the price and volatility at $t + 1$. This improves the quality of our price modeling process significantly. Since the trading strategies tested in this model are implemented using closing prices, there is no risk of look-ahead bias since at the close of day t we know today's price. We use this to model the price and volatility paths for the next t days. In our standard configuration we "reset" the modeling process every 10 days.

1.5 Trading Strategies

Momentum and trend-following strategies are empirically supported by a variety of academic studies across asset classes, industries, time periods, and specifications (see Jegadeesh and Titman (1993), Chan et al. (1996), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Lee and Swaminathan (2000), and Asness et al. (2013)). They are also one of the most widely applied trading strategies in the financial industry (see for example Granger et al. (2014)). A famous trend-following strategy with its roots in technical analysis is the moving average cross. This strategy serves as the benchmark in this paper and we try to outperform it in terms of Sharpe ratio and maximum drawdown.

1.5.1 Moving Average Cross

We start by explaining the underlying logic behind our benchmark strategy, the moving average cross, and how it works. As the second word suggests, it uses an average of a specific range of data. In our base case we use a moving average of 50 days. This means that we calculate the average price of the last 50 observed closing prices for a specific asset. As the first word implies, this average price moves–in other words, as soon as we have a new observed closing price in our data, we add this to the average calculation and drop the first observation used in the last average calculation. Using again the 50 days moving average, each day the newest closing price is added to the total and the closing price 51 days back is removed. Formally, the moving average can be written as

$$MA_{k_1} = \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1}. \tag{1.15}$$

where k_1 = moving average period.

Visually, the averaged price series results in a smoother line from which a trend can be identified more easily. Figure 1.1 indicates this by plotting the price series in black, a 50 days moving average in red, and a 200 days moving average in blue.

The moving average cross system can also be found in the literature under the name of double crossover method. This term is used to explain that a buy signal is generated when the faster moving average crosses the slower moving average from below. One of the most famous calibrations is called the Golden/Death Cross, and is a slow trend-following strategy using a 50 days moving average for the fast, and a 200 days moving average for the slow period. A buy signal is generated when the 50 days average crosses to above the 200 days average (Golden Cross). This scenario implies an uptrend, whereas a reversed signal (the 50 days moving average crosses the 200 days moving average from above) signals a downtrend and is called the Death Cross. This double crossover strategy lags more than a strategy that is based on the closing price and only one moving average series, but as both series used to generate signals are smoothed, the strategy does not get caught if prices whipsaw. Formally, this can be stated as follows:[4]

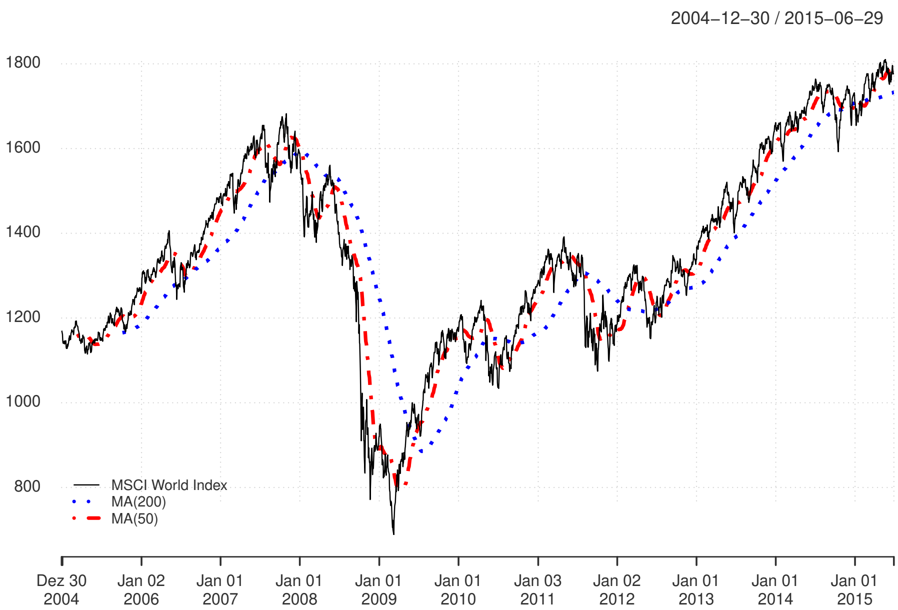
$$Long: \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1} > \sum_{v=-k_2+1}^{0} \frac{P_{t+v}}{k_2}. \tag{1.16}$$

with moving average periods $0 < k_1 < k_2$.

As mentioned above, the moving average cross is a trend-following strategy that has the purpose of identifying the begin of a new or the end of an existing trend. Looking at a moving average plot is similar to using trendlines in technical analysis. The moving average strategy, however, is a lagging signal. Murphy (1999) puts it this way: “Its purpose is to track the progress of the trend. The moving average is a follower, not a leader. It never anticipates; it only reacts. The movÂing average follows a market and tells us that a trend has begun, but only after the fact.” The shorter the moving average period chosen, the closer the filtered series follows the price series. Additionally, a shorter moving average period implies a reduced time lag until the signal is generated. On the other hand, shorter moving average periods are more sensitive to price movements. Since the strategy averages the information contained in the price, it has similar properties to many other econometric filters used in economics and finance (see for example Pedersen (2010)): it is used as a smoothing device to filter noise from the data. This trading strategy is found to be a better timing instrument than other momentum strategies such as the time-series momentum strategy of Moskowitz et al. (2012) (see Marshall et al. (2014)). It therefore serves as the benchmark strategy for the model tested in this paper.

[4]As our baseline backtests are conducted in a long-only trading environment we only provide the construction methods for long signals. The complete documentation for long–short signals can be found in the online appendix.

Figure 1.1: Moving Average Cross: This chart shows the price series of the MSCI World Index together with two moving averages. The chosen calibration is the same as in our baseline model with a fast-moving average of 50 days colored in dash-dotted red, and a slow-moving average of 200 days colored in dotted blue. The strategy is long if the dash-dotted red series is above the dotted blue series. Visually, the strategy seems to be a good indicator for trend detection with the drawback of being lagging by construction.



1.5.2 Median Moving Average Cross

We develop a hybrid from the moving average cross strategy that is based on our simulated prices resulting from the scenario generating process. The strategy follows the logic and parametrization used in the moving average cross strategy, but is applied on the median of our simulated prices. The strategy is implemented as follows: We calculate the cross-sectional median of all simulated prices, P^{SBP}. The resulting, more robust, simulated price is then smoothed using the fast- and slow-moving averages. The strategy follows the same logic as the moving average cross strategy and therefore is long if the fast-moving average of the median simulated price crosses the slow-moving average of the median simulated price from below. In contrast to the benchmark strategy, which looks at today's closing price to determine tomorrow's positioning, the median moving average cross looks at tomorrow's simulated price to generate trading signals for tomorrow. Formally, this can be stated as

$$Long : MA_{k1}(\tilde{x}_{0.5}(P_{1,N}^{SBP})) > MA_{k2}(\tilde{x}_{0.5}(P_{1,N}^{SBP}). \tag{1.17}$$

where $\tilde{x}_{0.5}$ is used as notation for median, SBP stands for the scenario building process, and $P_{1,N}^{SBP}$ indicates the simulated price series starting with the first simulated price path, P_1^{SBP}, and ending with the last simulated price path, P_N^{SBP}.

We use the terms median moving average cross and median simulated price cross interchangeably.

1.5.3 Probability Strategy

The second strategy we develop based on our simulated prices is the probability strategy. What is important for a trader today is the probability of an asset price rising or falling in the days ahead; in other words, the probability of a positive or negative future return. To determine this probability the trader would have to assume a return distribution. As with the scenario generating process described above, we generate hundreds of simulated prices with similar statistical properties as the observed price. These simulated prices can be used to calculate the probability of positive/negative returns based on the empirical distribution of past returns and therefore without the need to specify a theoretical distribution to calculate this probability. We define the probability as

$$\Pr(r_{t+1} > x\%) = \frac{\sum_{n=1}^{N} \left(r_{t+1,n}^{SBP} > x\% \right)}{N}. \tag{1.18}$$

where N is the number of simulated price paths, $r_{t+1,n}^{SBP}$ is the simulated logarithmic return at time t for the period $t+1$ from simulation run n, and $x\%$ is the chosen return threshold.

In addition to entering a trade, the trader can also determine the probability threshold—that is to say, a long position is opened, if the probability of a return larger than $x\%$ over the next n days is larger than (or equal) to $y\%$; therefore:

$$Long : \Pr(r_{t+1} > x\%) \geq y\%. \tag{1.19}$$

where, as described above, $x\%$ is the return threshold and $y\%$ represents the specified probability

threshold.
In our baseline configuration we set the probability target, $y\%$, equal to 50 percent, but impose a greater-than restriction instead of a greater-than-or-equal-to restriction.

1.6 Performance Evaluation

To compare the empirical results of our backtests we evaluate the performance of our trading strategies using two metrics. The first metric is the Sharpe ratio, which is used as a risk-adjusted return measure, with our second metric—maximum drawdown—we focus purely on the losses experienced when applying a strategy.

1.6.1 Sharpe Ratio

The Sharpe ratio is defined as the strategy j's mean of excess returns over the risk-free asset, $\hat{\mu}_j$, divided by its standard deviation, $\hat{\sigma}_j$. Formally, the Sharpe ratio for strategy j is defined as

$$\widehat{\mathrm{SR}}_j = \frac{\hat{\mu}_j}{\hat{\sigma}_j}. \tag{1.20}$$

1.6.2 Maximum Drawdown

Maximum drawdown is defined as the largest drop from peak to trough over a certain period of time, $[0, T]$. Mathematically speaking, if $v_t(x)$ is the net asset value of a trading strategy at time t, the drawdown function at time t is defined as the difference between the maximum of this function and the value of this function at time t. From the drawdown function, the maximum drawdown can be determined by choosing its maximum value over the entire time interval, $[0, T]$.
Formally, the maximum drawdown of strategy j is defined as

$$\mathrm{MDD}_j = \max_{0\leq t\leq T}\left(\frac{\max_{0\leq\tau\leq t}[v_\tau(x)] - v_t(x)}{\max_{0\leq\tau\leq t}[v_\tau(x)]}\right)\cdot(-1)\,. \tag{1.21}$$

1.7 Data & Empirical Results

The price data we test in this paper was collected from the Bloomberg Terminal with daily frequency over a time period from December 2004 until June 2015.
This chapter shows the empirical results for two assets: the MSCI World Index and the Standard & Poor's 500 Index. The empirical results for other assets and a variety of robustness checks will be provided upon request and will be collected and documented in our online appendix. [5]

1.7.1 Parameter Settings

Figure 1.2 shows the parameters used in our backtests. The baseline model uses a moving average specification of 50 days for the fast period and 200 days for the slow period. We simulate 200 alternative price paths and reset the simulation process every ten days. We use GARCH(1,1) as

[5] Link to online appendix.

our volatility model in the baseline model. We also implement a volatility model detector that automatically detects the best explaining model and applies it. For illustrative purposes and ease of use we provide the results using the most basic model. Additionally, Hansen and Lunde (2005) find that among 330 different models none predicts volatility significantly better than GARCH(1,1). Other parameter combinations can be found in the appendix to this paper, where the robustness checks are presented.

Path simulations	200
Price ahead simulations	10
MA, fast	50
MA, slow	200
Model type	GARCH(1,1)
Strategy type	Long only

Figure 1.2: This table shows the standard configuration used for the empirical tests.

1.7.2 Price Simulations

Before discussing the empirical results of our backtested trading strategies we would like to focus on the scenario building process itself and the resulting simulated prices. We can clearly recognize that overall our simulation results are in line with the development of the observed price series. This follows from the fact that our simulated price paths oscillate around the observed price series, as can be seen in Figure 1.3, where we plot the observed MSCI World price series in black and the simulated price series in pink. Since we simulate 200 artificial price paths in our baseline model, our simulated prices also show deviations from the observed price. To reduce these deviations we calculate the median of all simulated price paths and compare this price series to the observed price. Again the structure is very similar to the observed price series. For a more detailed examination of this result we provide Figure 1.4, which plots both series–the observed price in black and the median of our simulated prices in dotted pink. To capture the relationship between either the observed price and the median of our simulated prices or the observed price and all simulated price paths, we report the correlation coefficients. First we calculate the average correlation coefficient between the observed and each simulated price using both the Pearson and the Spearman approach. Both metrics are very high, with a correlation coefficient of 0.985 each. The correlation coefficients between the median of our simulated prices and the observed price are 0.985 using Pearson's and 0.984 using Spearman's approach. We observe stronger deviations from the observed price in times of high volatility, where our simulated prices fluctuate slightly more widely around the observed price series.

Figure 1.3: Observed and Simulated Prices: This figure, based on the MSCI World Index, shows the simulated price paths resulting from our scenario building process in pink, and the observed price series in black.

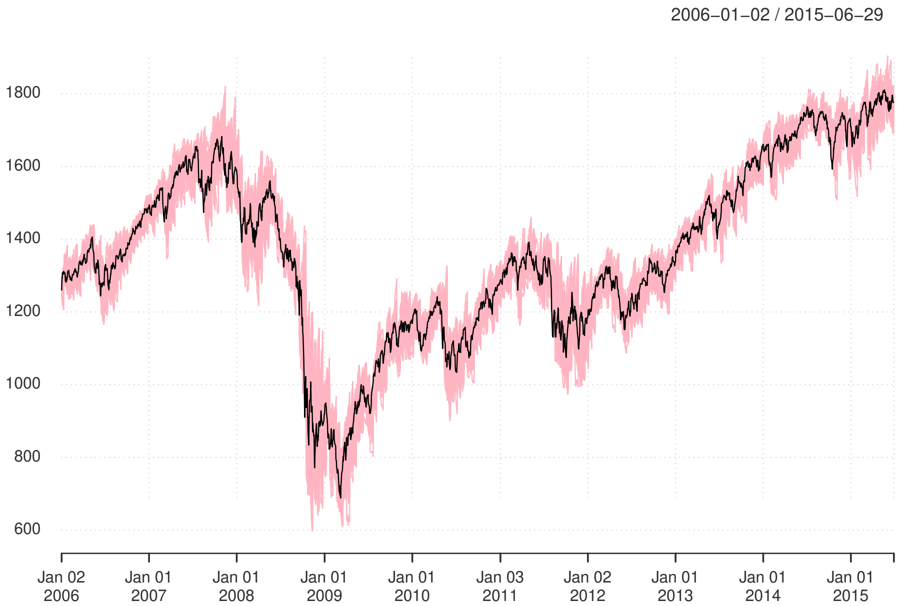


Figure 1.4: Observed and Median Simulated Price: In this figure, based on the MSCI World Index, we plot the median simulated price resulting from our scenario building process in dotted pink together with the observed price in black.

1.7.3 Equity Case–MSCI World

We use the MSCI World Index as the underlying asset for the backtests of our equity case. The MSCI World Index contains large- and mid-cap companies spread over more than 20 developed markets countries. Having more than 1,500 constituents, the index covers approximately 85 percent of the market capitalization in each country. To visualize our empirical findings, we provide Figures 1.5 and 1.6; the first shows the cumulative return generated by the respective trading strategy. In each of these figures we plot four data series: the black series is the buy-and-hold strategy, which buys the asset at $t = 0$ and holds it until $t = T$. This is plotted for illustration purposes only, as we do not try to outperform the buy-and-hold strategy. We will nonetheless refer to the buy-and-hold strategy if such reference is beneficial. The red series is the moving average cross strategy, the blue line represents the median simulated price strategy, and the green line represents the probability strategy.
As can be seen in the Figure 1.5, the probability-based strategy achieves the highest cumulative return. The strategy benefits significantly from its ability to correctly predict the market stress generated during the financial crisis. In contrast to the buy-and-hold strategy, the probability strategy is able to circumvent the large drawdowns of 40–60 percent as can be seen in Figure 1.6. The probability strategy does not capture the recovery of asset prices to the same extent as does the buy-and-hold strategy. The probability strategy continues to outperform the buy-and-hold and the benchmark strategies until the end of the data sample, mainly—as in the example explained above—due to its ability to predict coming market stress. The probability strategy is, by its nature, a defensive strategy, with the primary goal of avoiding drawdowns. Therefore, it does not react as strongly to market recoveries as the underlying asset itself, but in terms of its Sharpe ratio strongly outperforms the buy-and-hold as well as the benchmark strategy, the moving average cross. All this results in a Sharpe ratio for the probability strategy that is almost 35 percent larger relative to our benchmark strategy. The behavior of the median moving average cross is very similar to that of the probability strategy over the entire testing period. They were able to avoid the huge drop in the price level caused by the financial crisis but not as well as was the benchmark strategy. The strategies based on simulated prices are, however, able to better catch the market recovery than the benchmark strategy. In contrast to during the financial crisis, both simulation-based strategies perform better than the benchmark strategy in the mid-2011 market correction. This outperformance is the fundament for the better risk-return properties of our simulation-based strategies. In addition, both strategies perform better at the end of 2014 until the end of our data sample, which leads to even stronger backtesting results in favor of the median moving average cross and the probability strategies. The median moving average cross generates an outperformance of 31 percent in terms of its Sharpe ratio relative to our benchmark. The maximum drawdown of both the probability and the median simulated price strategy is 25%. This is a reduction of 5% or almost 14% relative to the benchmark strategy.

Figure 1.5: Cumulative Return: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; whereas the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast-, and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

Figure 1.6: Drawdown: This chart shows the maximum drawdown of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; whereas the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast-, and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	0.1024	0.2979	0.4006	0.3905
	(0.280)	(0.146)	(0.087)	(0.092)
Annualized Return	0.0184	0.0315	0.0428	0.0417
Annualized Std Dev	0.1799	0.1057	0.1069	0.1069
Maximum Drawdown	0.6173	0.2917	0.2487	0.2454

Figure 1.7: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index. The moving averages are specified as follows: the slow-moving average is equal to 200 and the fast-moving average is equal to 50. The time period tested is from 2006-07-14 to 2015-06-29. Number of simulations is equal to 200, with number of steps equal to 10.

1.7.4 Equity Case–Standard & Poor's 500

We use the S&P 500 Index as the underlying asset for the backtests of our equity case. The S&P 500 includes 500 stocks of leading large-cap US companies and captures approximately 80 percent of the available market capitalization. To visualize our empirical findings, we provide Figures 1.8 and 1.9. The first shows the cumulative return generated by the respective trading strategy; the second plots and compares the drawdowns each strategy experiences. Clearly, the trading strategies based on our simulated prices outperform the benchmark strategy in terms of cumulative return. The behavior of all tested trend-following strategies is very similar in terms of cumulative return as well as in terms of drawdowns. However, in spring 2010 the simulation-based strategies are able to close their positions at a better time than the benchmark strategy does, and the benchmark strategy loses significantly more, as can be seen in Figure 1.9. Afterward, the signals created by the three trading strategies are approximately identical until mid-2011, when the benchmark strategy leaves its long position open for too long. In contrast, both simulation-based strategies close out their long positions earlier resulting in a lower drawdown in this period. This again results in amplified outperformance relative to the benchmark strategy. These findings, translated into numbers, are provided in Figure 1.10. It contains the annualized Sharpe ratios for our tested trading strategies. The median moving average cross strategy achieves the highest Sharpe ratio with 0.8022, or, 14 percent higher than the benchmark's Sharpe ratio. The probability strategy has a Sharpe ratio of 0.7997, which is almost as high as the median moving average cross strategy. As can be seen in Figure 1.10, the outperformance is due to the higher annualized return, whereas the volatility of both simulation-based strategies is slightly higher than that of the benchmark strategy. But as the volatilities of all three trend-following strategies are almost equal and we do not focus on standard deviation as our risk-measure, we move to the maximum drawdown figures in the last row of the same table. It is important to notice that the benchmark strategy reduces the maximum drawdown by approximately 65 percent relative to the buy-and-hold strategy even though its main disadvantage is its lagging behavior in terms of trading signal generation. The simulation-based strategies both experience a maximum drawdown of 18 percent which is a 10% reduction relative to the benchmark strategy.

Figure 1.8: Cumulative Return: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; whereas the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the S&P 500 Index. The tested strategies are based on a moving average parametrization of 50 days for the fast-, and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

Figure 1.9: Drawdown: This chart shows the maximum drawdown of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; whereas the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the S&P 500 Index. The tested strategies are based on a moving average parametrization of 50 days for the fast-, and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe ratio	0.2710	0.6996	0.7997	0.8022
	(0.131)	(0.013)	(0.006)	(0.006)
Annualized Return	0.0568	0.0862	0.0999	0.1002
Annualized Std Dev	0.2096	0.1232	0.1249	0.1249
Maximum Drawdown	0.5962	0.2007	0.1803	0.1803

Figure 1.10: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset S&P 500 Index. The moving averages are specified as follows: the slow-moving average is equal to 200 and the fast-moving average is equal to 50. The time period tested is from 2006-07-14 to 2015-06-29. Number of simulations is equal to 200, with number of steps equal to 10.

1.8 Robustness

In Chapter A we report the conducted robustness checks to challenge the main findings in this paper. These robustness checks include a sensitivity analysis of the chosen parametrization of our trading strategy, a subsample test, as well as long–short and short–only backtests. On top of these robustness checks which target the trading strategy itself, we challenge the scenario building approach itself by altering the number of price simulations and days-ahead price simulations. The sensitivity analysis related to the chosen lookback period supports our main findings, as the probability and the median moving average cross strategy both still outperform the benchmark strategy. We detect, however, that the drawdown figures (for all active strategies) are affected by shortening the chosen smoothing period. This makes intuitively sense, as the shorter smoothing period implies more noise contained in the signal-generating series. The chosen period for our subsample analysis was challenging: it contains the financial crisis and the recovery thereafter. While the buy-and-hold strategy generates a negative Sharpe ratio over this period, both simulation-based strategies generate significantly higher Sharpe ratios relative to benchmark, the moving average cross strategy. The results presented in the main paper, based on a long–only trading environment are robust, even when we change to long–short or short–only: the simulation-based strategies achieve the highest Sharpe ratio, as their annualized return is significantly higher as the annualized return of the benchmark strategy while keeping the volatility at comparable levels. To challenge the dependency of our scenario building process on our chosen input parameters, we increase the number of simulated price series by quadrupling it. The empirical results for these backtests support our main findings, documenting the performance improvement of our simulation-based strategies compared to the moving average cross strategy in terms of Sharpe ratio and maximum drawdown. We alter the days-ahead price simulations to test the robustness of our findings with regard to the predictive power of our model. We clearly find, that the shorter the days-ahead simulations, the better the results. Therefore, our results support the simulation of few days-ahead. Overall, the conducted robustness checks support the findings of our main paper.

1.9 Conclusion

In this paper we simulate alternative price paths based on the observed, empirical distribution of past returns. This allows us to circumvent the problem of pre-specifying a distribution function that our simulated returns have to follow. This scenario building process is therefore distribution agnostic. Our empirical results suggest that using a simulation process that is able to capture the characteristics of a price and volatility series it is possible to improve trend-following trading strategies. Based on our simulated prices we develop two trading strategies: the probability strategy looks at the probability of tomorrow's return being larger than a specified threshold, whereas the median simulated price strategy uses the median of all simulated prices and generates trading signals with the same logic as does the benchmark strategy, the moving average cross system. However, the probability and the median simulated price strategy use tomorrow's simulated price data to create tomorrow's trading signal, which is then traded on the underlying asset. We test our trading strategies against the moving average cross system, which is widely applied in the financial industry (see Brock et al. (1992)). Our results are stable across a variety of chosen parametrizations and, more important, across several assets. The methodology presented in this paper is able to improve the existing trend-following strategy, the moving average cross, in terms of both Sharpe ratio and maximum drawdown. Both trading strategies, the probability and the median simulated price strategy, are able to detect increased market stress and therefore outperform the benchmark strategy. Especially either in times of high volatility or when, by its nature, an asset exhibits high volatility, the probability and the median simulated price strategy are able to reduce drawdowns. This leads to their significant outperformance relative to the benchmark strategy. We test our methodology on various assets and report the empirical findings for an equity investment in the MSCI World and in Standard & Poor's 500 Index. Additionally, we conduct several robustness checks in order to challenge the main findings of our baseline results. The empirical results of our robustness checks support our main findings. Even though our strategies outperform the buy-and-hold strategy most of the time, it is important to recall that this is not the goal of this paper. Our strategies have to outperform the moving average cross system using the same specification as the benchmark strategy. We therefore do not adjust the moving average cross parametrization to better fit a specific asset. Our only goal is to improve the trend-following strategy. Fitting the strategy calibration to the price series to improve the performance and exposing our results to possible curve fitting is not our intention and is left to the trader if desired. We provide a methodology that can be widely applied to improve strategies and make them more robust for a large universe of assets.

Acknowledgments

I would like to thank my advisor Karl Schmedders as well as Andrea Laurent for their support and guidance during this project. I would also like to thank the seminar audiences at the 2016 Initiative for Computational Economics at Stanford University and at the 4th Young Finance Scholars Conference at the University of Sussex, particularly Kenneth Judd and Carol Alexander, for helpful comments and suggestions.

A Appendix: Chapter 1

A.1 Important Formulas

In this section we provide the most important formulas used in our paper. In contrast to our main paper, which reports the long-only empirical results, this appendix contains additional long–short and short-only backtests and therefore also the respective formulas. In Subsection A.1.1 we provide both the long and short formulas for every tested trading strategy.

A.1.1 Trading Strategies

A.1.1.1 Moving Average Cross

$$MA_{k_1} = \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1}, \tag{A.1}$$

where k_1 = the moving average period.

$$\textit{Long}: \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1} > \sum_{v=-k_2+1}^{0} \frac{P_{t+v}}{k_2} \text{ and,} \tag{A.2}$$

$$\textit{Short}: \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1} < \sum_{v=-k_2+1}^{0} \frac{P_{t+v}}{k_2}, \tag{A.3}$$

with moving average periods $0 < k_1 < k_2$.

A.1.1.2 Median Moving Average Cross

$$\textit{Long}: MA_{k1}\big(\tilde{x}_{0.5}(P_{1,N}^{SBP})\big) > MA_{k2}\big(\tilde{x}_{0.5}(P_{1,N}^{SBP}\big) \text{ and,} \tag{A.4}$$

$$\textit{Short}: MA_{k1}\big(\tilde{x}_{0.5}(P_{1,N}^{SBP})\big) < MA_{k2}\big(\tilde{x}_{0.5}(P_{1,N}^{SBP}\big), \tag{A.5}$$

where $\tilde{x}_{0.5}$ is used as notation for median, SBP stands for scenario building process, and $P_{1,N}^{SBP}$ indicates the simulated price series starting with the first simulated price path, P_1^{SBP}, and ending with the last simulated price path, P_N^{SBP}.

A.1.1.3 Probability Strategy

$$\Pr(r_{t+1} > x\%) = \frac{\sum_{n=1}^{N} \left(r_{t+1,n}^{SBP} > x\% \right)}{N}. \tag{A.6}$$

where N is the number of simulated price paths, $r_{t+1,n}^{SBP}$ is the simulated logarithmic return at time t for the period $t+1$ from simulation run n, and $x\%$ is the chosen return threshold.

In addition to entering a trade, the trader can also determine the probability threshold—that is to say, a long position is opened, if the probability of a return larger than $x\%$ over the next n days is larger than (or equal) to $y\%$; therefore:

$$Long : \Pr(r_{t+1} > x\%) \geq y\%, \tag{A.7}$$

where, as described above, $x\%$ is the return threshold and $y\%$ represents the specified probability threshold.

$$Short : \Pr(r_{t+1} > x\%) < y\%, \tag{A.8}$$

where, as described above, $x\%$ is the return threshold and $y\%$ represents the specified probability threshold.

A.2 Parameter Settings

Exhibit A.1 shows the parameters used in our backtests. The baseline model uses a moving average specification of 200 days for the slow period and 50 days for the fast period. The other combinations can be found in Section A.3, where some robustness checks are presented. We conduct robustness checks by altering the following specification, set in italics:

MA, fast	*5*, *10*, 50
MA, slow	*20*, *50*, 200
Sample period	07/2006–06/2015, *01/2005–12/2011*
Strategy type	L, *LS*, *S*
Path simulations	200, *800*
Price ahead simulations	10, *15*, *20*, ..., *100*

Figure A.1: This table shows the alternative configurations used for the empirical tests.

A.3 Robustness Checks

In this section we share additional insights into the results of our empirical analysis. The robustness checks presented in this section are based on the equity case using the MSCI World Index as in the first reported results in the main paper.

A.3.1 (10, 50) Specification

The results for the (10, 50) specification support our findings from the baseline model, where we use a moving average parametrization of (50, 200). As in our baseline results, the trading strategies based on our simulated prices outperform the benchmark, the moving average cross strategy. In this case, the Sharpe ratio is even more significantly different than in the baseline results. The effect is amplified when looking at the annual Sharpe ratios, which are now 26 percent (probability strategy) and 41 percent (median simulated price) higher compared to the benchmark's Sharpe ratio. This is also mirrored in the drawdown statistics: Whereas the benchmark strategy reduces the maximum drawdown from 62 percent in the buy-and-hold strategy to 27 percent, which is a reduction of slightly more than 56 percent, our strategies reduce the drawdowns even more. Compared to the benchmark strategy, our strategies are able to reduce the maximum drawdown even further from 4 percent up to more than 10 percent. Even though our benchmark is not the buy-and-hold strategy, this translates into a drawdown reduction of between 58 percent and 61 percent..

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	0.1399	0.2421	0.3073	0.3409
	(0.235)	(0.176)	(0.128)	(0.107)
Annualized Return	0.0243	0.0249	0.0323	0.0359
Annualized Std Dev	0.1738	0.1028	0.1052	0.1053
Maximum Drawdown	0.6173	0.2740	0.2641	0.2431

Figure A.2: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index in a long-only environment. The moving averages are specified as follows: the slow-moving average is equal to 50 days and the fast-moving average is equal to 10 days. The time period tested is from 2004 to 2015. The number of simulations is equal to 200, with the number of steps equal to 10.

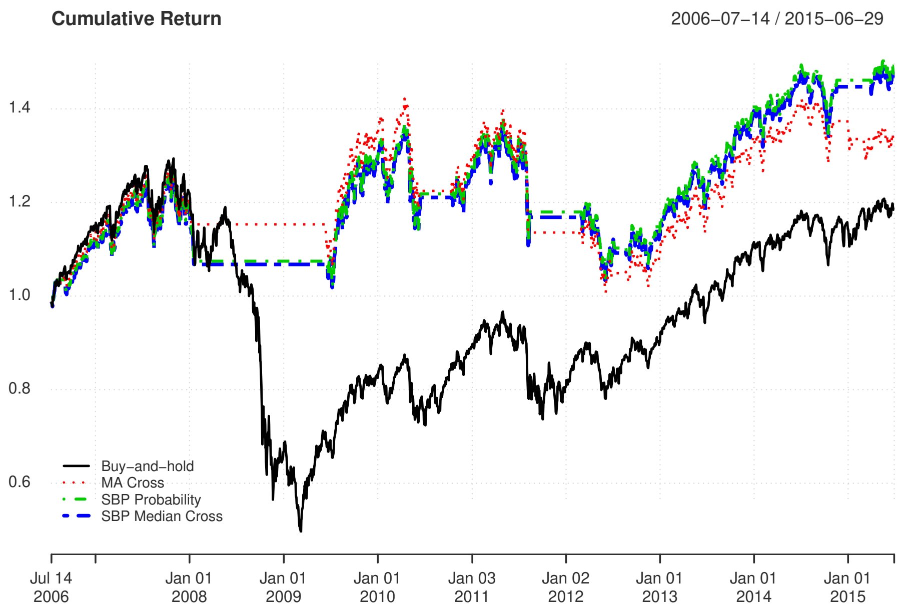


Figure A.3: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 10 days for the fast- and 50 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

Figure A.4: This chart shows the maximum drawdown of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 10 days for the fast- and 50 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

A.3.2 (5, 20) Specification

The specification using a fast-moving average period of 5 days and a slow-moving average period of 20 days results in a lower Sharpe ratio and higher maximum drawdown for our benchmark strategy compared to our baseline model results. For the benchmark strategy, using a (50, 200) moving average specification leads to a Sharpe ratio which is two times larger than the Sharpe ratio reported in this robustness check. This is in contrast to the achieved Sharpe ratio of the probability strategy that is 5 percent higher relative to the baseline Sharpe ratio. The median simulated price strategy still achieves a 3 percent higher Sharpe ratio relative to the Sharpe ratio reported in our baseline results. In terms of drawdowns, the benchmark strategy suffers from a 13 percent increase in drawdown relative to the worst drawdown generated in our baseline results. This is also true for our proprietary strategies: the probability strategy has an increase in the worst drawdown statistic of 4 percent relative to the baseline results and the median simulated price has an increased maximum drawdown of 18 percent relative to the baseline results. Compared to the (10, 50) specification, the Sharpe ratio plunged more than 40 percent and the drawdowns increased by 22 percent. Due to the shorter smoothing periods the trading strategy enters trades more aggressively. These trades might be interpreted as short-term opportunities. However, the underlying price series are lacking a real, longer-term trend. This behavior does not seem to pay off in the benchmark case. In contrast to the benchmark case, our strategies exhibit only slightly higher drawdowns of at most 20 percent. In contrast to the benchmark case, the increased risk taken by entering short-term oriented trades pays off and is manifested in the higher Sharpe ratios of our trading strategies. The Sharpe ratio of the probability strategy rises more than 33 percent and the Sharpe ratio of the median simulated price strategy rises almost 20 percent.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	0.2381	0.1561	0.4715	0.4526
	(0.225)	(0.310)	(0.068)	(0.076)
Annualized Return	0.0258	0.0105	0.0430	0.0413
Annualized Std Dev	0.1730	0.1024	0.1021	0.1029
Maximum Drawdown	0.6173	0.3255	0.2641	0.2942

Figure A.5: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index in a long-only environment. The moving averages are specified as follows: the slow-moving average is equal to 20 days and the fast-moving average is equal to 5 days. The time period tested is from 2004 to 2015. The number of simulations is equal to 200, with the number of steps equal to 10.

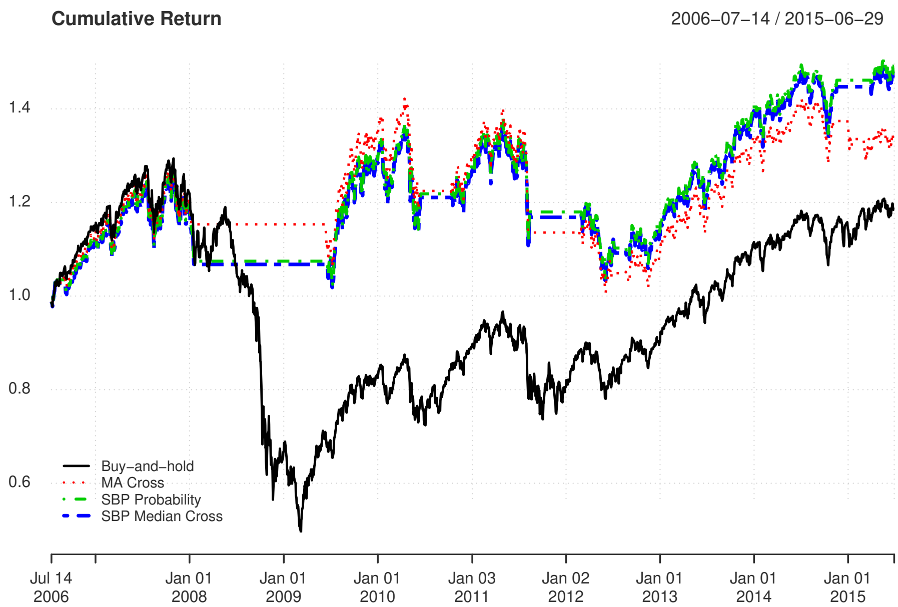


Figure A.6: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 5 days for the fast- and 20 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

Figure A.7: This chart shows the maximum drawdown of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 5 days for the fast- and 20 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

The robustness checks conducted using different moving average periods support our findings. Even though the strategies might exhibit higher drawdowns compared to the base-case example with a very slow-moving average configuration (recall that the slow-moving average period is almost one year of daily price observations), the Sharpe ratios of our trading strategies are significantly higher than the benchmark's Sharpe ratio. In addition, the maximum drawdown figures are nonetheless lower than those of the benchmark strategy, indicating that our trading strategies yield better results in terms of risk management but also risk-adjusted return generation, which would be reflected in performance metrics such as Sharpe, Calmar, and Sortino ratios. We will next discuss robustness checks using subsamples of our full data sample to test if the results persist even for other time periods that might include other investment regimes and fewer and/or other trends.

A.3.3 Subsample Testing

In this section we report and discuss the empirical results from our baseline configuration applied to a subsample of our original dataset using data from July 2006 until December 2011. We choose this period as a subsample because it was an extremely challenging environment for the financial markets. As we see in Exhibit A.9, there was an initial upward-trending market until the end of 2007, with a peak around July 2007 a short setback afterwards, only for the market to climb back to its previous heights in autumn 2007. Afterward, the markets entered a pronounced decline, which accelerated notably in autumn 2008. After reaching the trough at the beginning of 2009, the markets recovered and started regaining their losses from the financial crisis, with a strong uptrend environment with whipsaws that lasted until the end of our full dataset. Our chosen subsample is therefore challenging since we have the end of an uptrend, which is already slowly losing its dynamic, moving into a sideways market with an abrupt change in trend direction moving downward, only to—after the sharp correction in asset prices—trend upward again with more volatility in the markets than before. As reflected in both the chart and the Sharpe ratio statistics, the buy-and-hold strategy lost money in our subsample. It was therefore a bad environment for passive investors since the market was not able to regain the losses experienced in this period. However, the probability strategy and the median simulated price strategy were able to avoid the large losses resulting from the financial crisis. This is also true for the benchmark strategy, which performs slightly better until mid-2009 since it exits the market earlier than our proprietary strategies. All three strategies perform similarly in the uptrend following the financial crisis and are not able to fully capture the large gains the market generated. This is due to the fact that our baseline models work with a very lethargic moving average configuration of 50 and 200 days, which are lagging and only slowly adjusting to the newly existing uptrend. From a risk perspective all three strategies are able to avoid some of the whipsaws in the uptrend and therefore are more stable than the buy-and-hold strategy. Especially after January 2011, where the MSCI World Index lost more than 15 percent, the three trading strategies react desirably and close their positions, while particularly our probability and median simulated price strategies outperform the benchmark strategy by benefiting from a short upleg in the MSCI World Index before closing out the position. This interpretation is also reflected in the Sharpe ratio statistics, where the benchmark strategy has

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	-0.0573	0.2923	0.4214	0.4334
	(0.553)	(0.247)	(0.163)	(0.156)
Annualized Return	-0.0346	0.0262	0.0417	0.0431
Annualized Std Dev	0.2145	0.1118	0.1145	0.1145
Maximum Drawdown	0.6173	0.2012	0.1930	0.1969

Figure A.8: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index in a long-only environment. The moving averages are specified as follows: the slow-moving average is equal to 200 days and the fast-moving average is equal to 50 days. The time period tested is from 2005 to 2011. The number of simulations is equal to 200, with the number of steps equal to 10.

a Sharpe ratio of 0.2923 compared to the probability strategy, which has a Sharpe ratio of 0.4214, and the median simulated price strategy, with 0.4334. This translates into a relative Sharpe ratio outperformance of 40–48 percent. As our simulation-based trading strategies are also slightly better in terms of maximum drawdown than the benchmark strategy, the findings in this subsample analysis are in line with our other results.

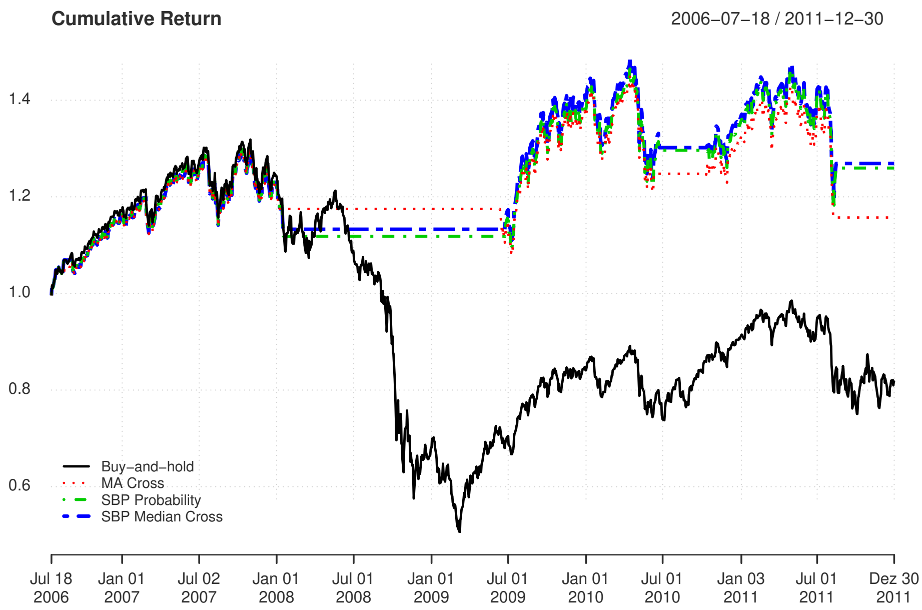


Figure A.9: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

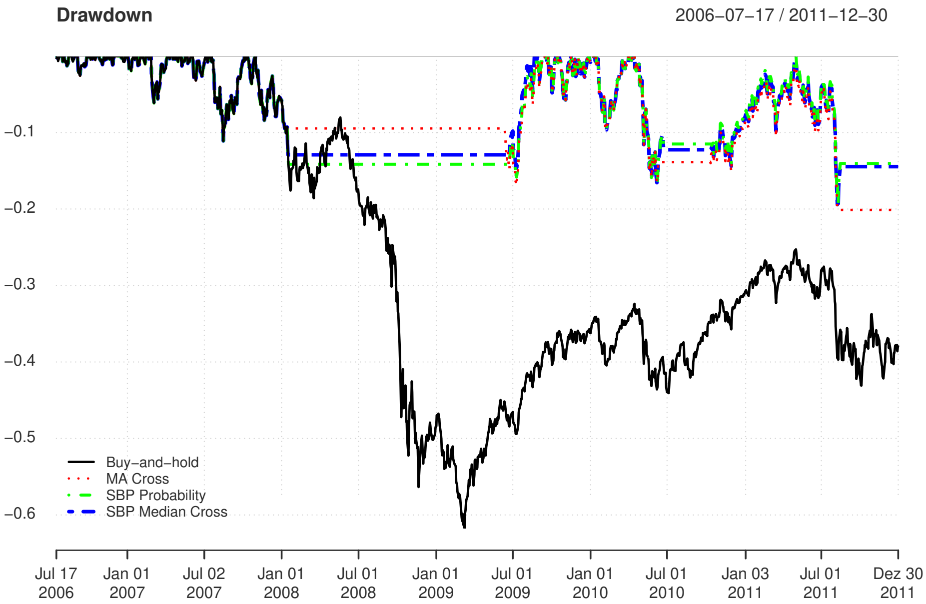


Figure A.10: This chart shows the maximum drawdown of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

A.3.4 Long–Short Strategy

In this robustness check we leave our long-only environment behind and backtest our strategy in a long–short environment. Since the buy-and-hold strategy is a long-only strategy by definition, we only provide the buy-and-hold results as a reference, but they cannot be directly compared to the other three strategies. The trend-following strategies generate signals as outlined in Subsection A.1.1.

It is important to bear in mind that the strategies are simply tested in a long–short environment without adding additional constraints with respect to signal generation. The probability strategy for instance could be extended such that the strategy also generates a market-neutral signal where it is not invested. This can be done by choosing a different threshold, $y\%$, for the short signal. In our long–short backtests the long and short thresholds are the same, therefore $x = y$.

Exhibit A.12 shows that all three trend-following strategies strongly benefit from the financial crisis and the heavy losses experienced by the underlying asset. In contrast to the probability and the median simulated price strategy, the benchmark strategy benefits most as it generates fewer false short signals at the very beginning of the financial crisis. Overall, all the trend-following strategies are able to generate good short signals in this period until the market reaches its trough. After having reached the trough, the trend-following strategies are once again unable to capture the immediate, strongly up-trending market and its associated gains. From the end of 2011 onward, the probability and the median simulated price strategy are able to perform similarly to the buy-and-hold strategy, whereas the benchmark strategy loses ground and—by the end of the dataset—only achieves a slightly higher cumulative return than the buy-and-hold strategy. But keep in mind that the buy-and-hold strategy cannot be compared directly and only serves as a reference. The fact that the benchmark strategy loses ground is also reflected in Exhibit A.13, where we clearly see that it experiences significantly higher drawdowns than our proprietary strategies do for a long time period. The Sharpe ratios of the probability and median simulated price strategies tell the same story. While the Sharpe ratio of our benchmark strategy is slightly higher than the buy-and-hold strategy, the probability strategy has a Sharpe ratio that is 35 percent higher and the median simulated price strategy achieves a Sharpe ratio which is 30 percent higher relative to the benchmark. Moving to the risk analysis, the benchmark strategy is able to reduce the drawdown to 57 percent, 8 percent lower than that of the buy-and-hold strategy. Relative to the benchmark, our proprietary strategies are able to reduce the worst drawdown by 20 percent. Summarizing this discussion, we can say that both the probability and the median simulated price strategy outperform the benchmark strategy in terms of Sharpe ratio and maximum drawdown in a long–short environment.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	0.1950	0.2187	0.3441	0.3323
	(0.280)	(0.256)	(0.152)	(0.160)
Annualized Return	0.0184	0.0228	0.0457	0.0435
Annualized Std Dev	0.1799	0.1799	0.1799	0.1799
Maximum Drawdown	0.6173	0.5731	0.4551	0.4586

Figure A.11: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index in a long–short environment. The moving averages are specified as follows: the slow-moving average is equal to 200 days and the fast-moving average is equal to 50 days. The time period tested is from 2004 to 2015. The number of simulations is equal to 200, with the number of steps equal to 10.

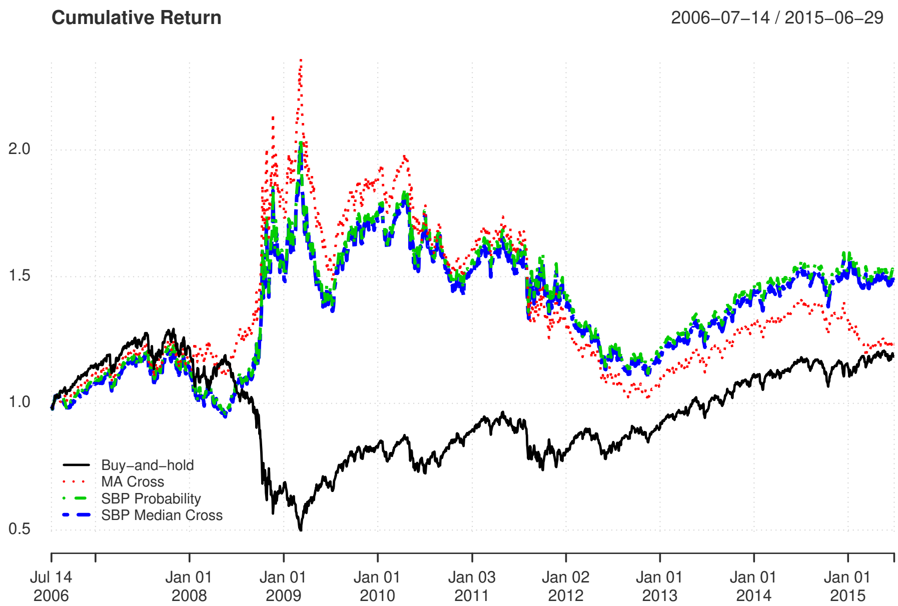


Figure A.12: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

Figure A.13: This chart shows the maximum drawdown of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

A.3.5 Short-Only Strategy

In this robustness check we stay away from our long-only environment and backtest our strategy in a short-only environment. Since the buy-and-hold strategy is a long-only strategy, we only provide the buy-and-hold results as a reference but–again–they cannot be directly compared to the other three strategies. Please refer to those of the Equations (A.3), (A.5), and (A.8) in Subsection A.1.1, where we explain how the trend-following strategies generate signals in a short environment. Keep in mind that the strategies are simply tested in a short-only environment without adding additional constraints with respect to signal generation. The probability strategy for instance generates a sell signal as soon as the probability of tomorrow's return being positive is less than a specified threshold. The threshold was not optimized for this short-only environment; neither was tomorrow's expected return specified differently to generate superior results: the Sharpe ratios clearly indicates the superiority of our probability and median simulated price strategies compared to the benchmark strategy—it is approximately six times larger than the Sharpe ratio of the benchmark strategy. The drawdown analysis is also in line with the previous results: The benchmark strategy experiences a maximum drawdown of 55 percent whereas our proprietary strategies are able to reduce the worst drawdown by 15 percent relative to the benchmark strategy. The results from the short-only backtests are therefore in line with the previously reported results.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	0.1950	0.0146	0.0926	0.0853
	(0.280)	(0.483)	(0.391)	(0.399)
Annualized Return	0.0184	-0.0084	0.0027	0.0017
Annualized Std Dev	0.1799	0.1456	0.1447	0.1447
Maximum Drawdown	0.6173	0.5484	0.4690	0.4707

Figure A.14: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index in a short-only environment. The moving averages are specified as follows: the slow-moving average is equal to 200 days and the fast-moving average is equal to 50 days. The time period tested is from 2004 to 2015. The number of simulations is equal to 200, with the number of steps equal to 10.

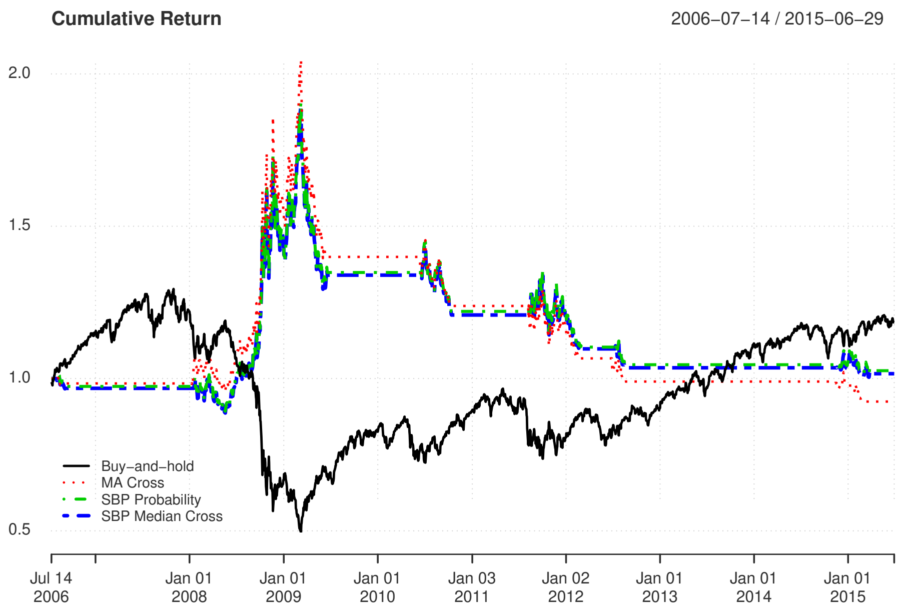


Figure A.15: This chart shows the cumulative return of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

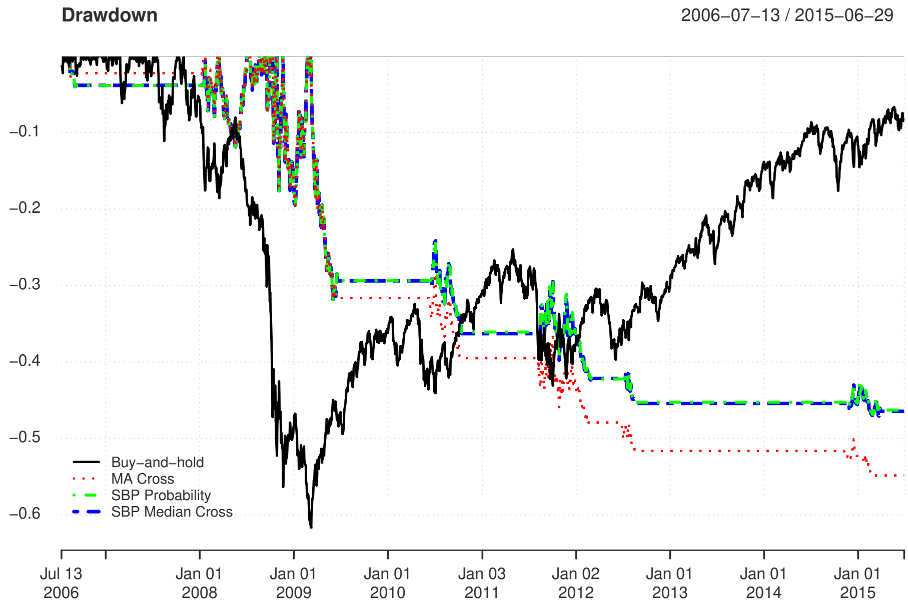


Figure A.16: This chart shows the maximum drawdown of four investment strategies: in black, the buy-and-hold strategy; the dotted red line represents the moving average cross, our benchmark strategy; the blue and green lines represent our simulation-based trading strategies, the median moving average cross and the probability strategy, respectively. This chart shows the equity case using the MSCI World Index. The tested strategies are based on a moving average parametrization of 50 days for the fast- and 200 days for the slow-moving average. We simulate 200 price paths using our adapted scenario building process.

A.3.6 Number Of Price Simulations

In this part of the robustness checks we quadruple the number of simulated alternative price paths from 200 to 800. We do this to make sure that the results do not depend on too few price simulations and therefore are not simulating the full empirical distribution of the asset price process. The results from this robustness check are in line with what we found previously: the Sharpe ratios of our strategies are between 28 percent and 30 percent higher than the benchmark case, whereas the worst drawdown can be reduced to between 83 percent and 86 percent compared to the benchmark strategy.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	0.1950	0.3523	0.4572	0.4527
	(0.280)	(0.146)	(0.086)	(0.088)
Annualized Return	0.0184	0.0315	0.0432	0.0427
Annualized Std Dev	0.1799	0.1057	0.1069	0.1069
Maximum Drawdown	0.6173	0.2917	0.2430	0.2463

Figure A.17: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index in a long-only environment. The moving averages are specified as follows: the slow-moving average is equal to 200 days and the fast-moving average is equal to 50 days. The time period tested is from 2004 to 2015. The number of simulations is equal to 800, with the number of steps equal to 10.

A.3.7 Days-Ahead Price Simulations

In this robustness check we alternate the number of price-ahead simulations which also changes the frequency of price adjustments. Recall that after every n days we use today's observed price to simulate the new price paths. In our baseline results we simulate ten days ahead. To test whether our results critically depend on the chosen parametrization of ten days, we challenge our findings by changing the days-ahead simulation. In this paper we report the backtesting results of two additional configurations; 50 days ahead and 5 days-ahead. We start with a discussion of the 50 days-ahead results.

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	0.1950	0.3523	0.3504	0.4131
	(0.280)	(0.146)	(0.147)	(0.108)
Annualized Return	0.0184	0.0315	0.0329	0.0399
Annualized Std Dev	0.1799	0.1057	0.1124	0.1119
Maximum Drawdown	0.6173	0.2917	0.3153	0.2986

Figure A.18: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index in a long-only environment. The moving averages are specified as follows: the slow-moving average is equal to 200 days and the fast-moving average is equal to 50 days. The time period tested is from 2004 to 2015. The number of simulations is equal to 200, with the number of steps equal to 50.

We would like to first compare the Sharpe ratio of the moving average cross system with that of our probability strategy. As we see in Table A.18, the Sharpe ratio of our probability strategy is slightly lower than that of the moving average cross. Even though the difference is not statistically significantly, we want to point out this fact. This is also mirrored in the maximum drawdown statistics, where the probability strategy experiences a 3 percent higher drawdown than the benchmark strategy. We explain this finding by the fact that, as described in the theoretical part of our main paper, it is possible that simulating longer time periods can lead to more extreme scenarios with strong drifts away from the observed price. We recall that the method applied in the present paper was developed for financial risk management, where extreme scenarios and price drifts can be positively interpreted in order to create a full empirical distribution based on historically observed statistical properties. Drifting artificial prices are not desirable in our case since we trade the original asset and not the asset's artificial price. We therefore advocate simulating only few prices into the future and resetting the price simulation

	Buy-and-hold	MA Cross	SBP Probability	SBP Median Cross
Sharpe Ratio	0.1950	0.3523	0.5222	0.5366
	(0.280)	(0.146)	(0.147)	(0.108)
Annualized Return	0.0184	0.0315	0.0501	0.0517
Annualized Std Dev	0.1799	0.1057	0.1063	0.059
Maximum Drawdown	0.6173	0.2917	0.2652	0.2613

Figure A.19: This table shows the Sharpe ratio (p-values in parentheses), annualized return, standard deviation, and maximum drawdown for the asset class equity and the asset MSCI World Index in a long-only environment. The moving averages are specified as follows: the slow-moving average is equal to 200 days and the fast-moving average is equal to 50 days. The time period tested is from 2004 to 2015. The number of simulations is equal to 200, with the number of steps equal to 5.

process to prevent the simulated asset prices to significantly drifting away from the observed price series. Our median cross strategy still achieves a Sharpe ratio 17 percent higher than that of the benchmark strategy. As this strategy relies on the median simulated price to create trading signals it is less sensitive to drifting simulated price series as, by definition, the median does not put too much weight on extreme scenarios, whereas in the probability strategy each simulated price series gets the same weight in the trading signal calculation. In particular, looking at the annualized Sharpe ratio figures shows that our strategy based on the median simulated price still has attractive properties compared to the benchmark strategy. To further investigate the strategies' sensitivity on the days-ahead price simulations we calculate the performance for a set of days-ahead specifications—namely, $\{5, 10, 15, \ldots, 90, 95, 100\}$. We plot the Sharpe ratio as a function of days-ahead price simulations in the next two figures (see Exhibit A.20). The first chart shows the resulting Sharpe ratio for the probability strategy and the second chart for the median simulated price strategy. The line indicates the regression slope when regressing the Sharpe ratio on the number of simulated daily prices. We clearly see that the Sharpe ratio declines with the number of days-ahead price predictions, which again supports our recommendation of simulating few prices and resetting the simulation process by using the observed price to reduce the probability of the simulated prices drifting too far away from the observed price series.

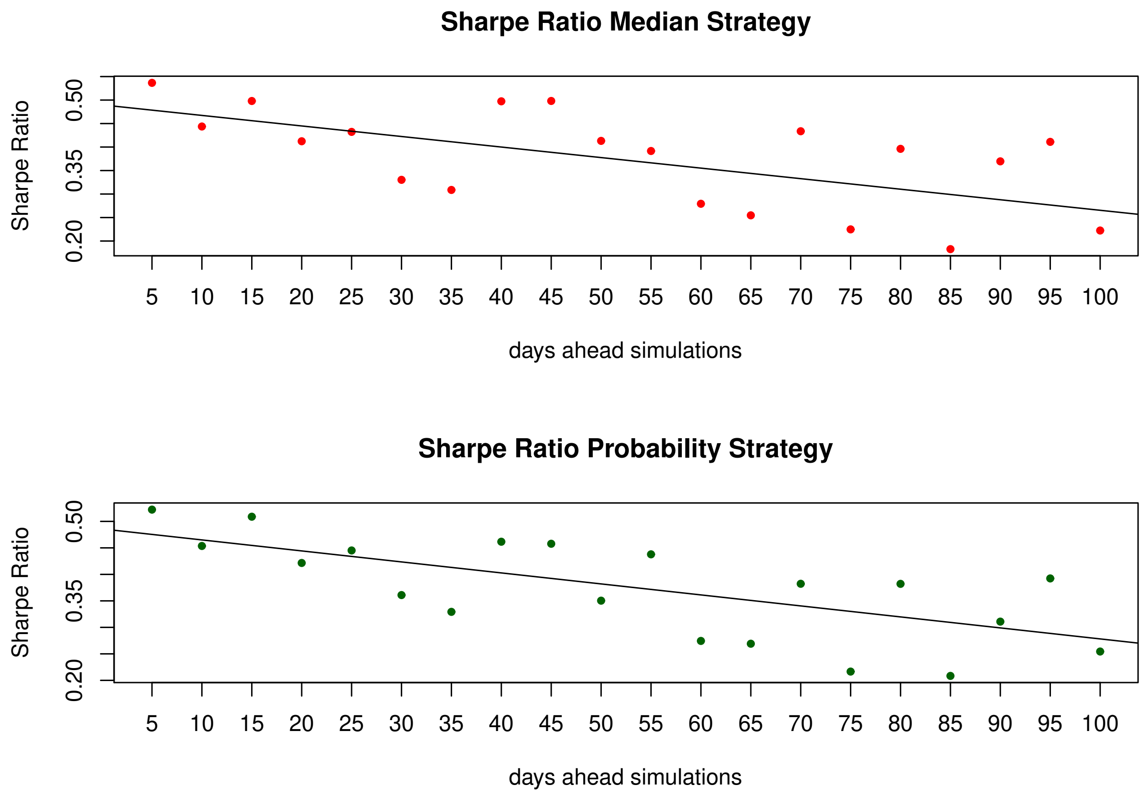


Figure A.20: This chart has two panes, each of which plots the Sharpe ratio of one of our two trading strategies as a function of the number of simulated daily ahead prices. Even though the Sharpe ratios fluctuate, we can clearly identify the property that the more days ahead we simulate our asset prices, the lower the Sharpe ratio gets. We tested a range of 5 to 100 days ahead.

2 Is Trading Indicator Performance Robust? Evidence from Scenario Building[1]

2.1 Introduction

Active trading and investment strategies have grown in popularity in recent decades both in academia and in the investment management industry. However, recent research shows that many active investment strategies with Sharpe ratios exceeding 2 are a pure result of luck and/or overfitting (see for example Bailey et al. 2017; Harvey and Liu 2015; Harvey et al. 2016). The focus of that research can be split into two groups: statistical adjustments to the reported Sharpe ratios due to multiple testing, and determining the probability of overfitting the strategies to the data—the latter otherwise known as data mining. One major problem when developing and backtesting active investment strategies is the limited existence of financial data with which to test the strategies. Splitting the available financial data into a testing sample (in-sample) and excluding some data for testing the behavior of the strategy on a pro forma out-of-sample is the standard way of dealing with the limited availability of data. As Bailey et al. (2017) show, this procedure does not properly fulfill the idea of out-of-sample testing, as the researcher knows the out-of-sample data and therefore can still reject a strategy if it performs badly. Additionally, leaving out the most recent data leads to a trading strategy that does not fully reflect the latest information available and therefore is based on old structures and regimes. As the price evolution of a financial asset is just one realization of a stochastic process out one of many possible histories, we simulate artificial prices with similar statistical properties as the observed price series. We build these alternative price paths in order to test the robustness of trading indicators. In particular, we apply a distribution-agnostic scenario building model that does not require a prior definition of the probability distribution of the return process. The scenario building model empirically explored in this paper is an extension of that of Barone Adesi et al. (1999), which they call filtered historical simulation. It combines the empirical distribution of past returns and nonlinear econometric models to simulate possible future values of an asset in the days ahead. From a statistical perspective it is a semi-parametric model. Using the empirical distribution of past returns implies that the price series is not assumed to conform any theoretical probability distribution. Our simulated prices are modeled such that memory is present in the data; this is an important regularity when working with financial data as they typically exhibit memory (i.e., economic cycles, reversal of financial flows, structural breaks, bubbles bursting, etc.)

This paper is organized as follows: We start with a theoretical part, Section 2.2, in which we

[1]This paper should be cited as Thomann, A. (2018), "Is Trading Indicator Performance Robust? Evidence from Scenario Building". A modified version of this paper has been submitted to the *Journal of Investment Strategies*.

explain the scenario building process applied in this paper. In two subsections we provide details of that process and explain the methodology used in this paper for simulating a single pathway (Subection 2.2.1) and for simulating multiple pathways of asset prices and variances (Subection 2.2.2). Section 2.3 contains the empirical part of our paper. We start with a description of our dataset used to test the trading indicators in this paper, continuing with a theoretical explanation of how the respective trading indicator is calculated and with the empirical results of our backtests, in Subections 2.3.3 and 2.3.4, respectively. We end our paper with the conclusions of our findings, presented in Section 2.5.

2.2 Scenario Building Process

Filtered historical simulation has been developed to avoid the drawbacks accompanying underlying historical simulation—its reliance on a specific distribution as well as the fact that it does not take into account empirical findings such as the existence of volatility clustering, fat tails, and the leverage effect (see Mandelbrot (1963) and Black (1976)). Its usage of past return indicates that the presented model originates from historical simulation. This historical return data is used as innovations to model the behavior of asset prices. Compared to historical simulation, its major enhancement is that the return is first adjusted by the volatility that was observed at that day and—in a second step—is multiplied by the forecasted volatility. This adjustment guarantees, that the past returns are stationary such that they are suitable innovations for the simulation process (see for example Posedel (2005) for a derivation of stationarity). The rescaling with volatility forecasts introduces the current market conditions to the past returns. The process described here in few words is explained in more detail and in a more formal way below.

Summarizing the benefits of using the approach of Barone Adesi et al. (1999), the most important point to emphasize is the fact that the data is not forced to originate from a theoretical, pre-specified distribution. Fat tails, volatility clusters, and changing means are all peculiarities that are allowed in this model—as it is based on the empirical distribution. We therefore take most of the empirical volatility modeling findings into account when building our artificial price and volatility paths. The model is able to handle dependencies across a very large set of assets without estimating the correlation matrix, and therefore has interesting properties from a computational perspective. It is possible to build scenarios in which simulated asset prices result from large returns following other large returns. We interpret such a scenario as an extreme scenario that might possibly not be included in the raw data as such. On the other hand, even though we break up existing autocorrelation, this scenario building process allows the generation of new trends that our trading strategies try to exploit. We see this as an additional advantage compared to historical simulation as this also moderates the requirements with respect to our dataset to include every possible scenario. To demonstrate how the scenario building process works, we follow the example of Barone Adesi et al. (1999) and first explain the simulation of a single pathway and afterwards of multiple pathways.

2.2.1 Scenario Building for a Single Pathway

Simulating a single pathway for one asset is less complicated and therefore helps us to understand the underlying methodology and how it is applied to data. The two most important variables we have to specify in the scenario building process are the number of simulation runs we want to perform (the number of artificial price paths we want to simulate) and the number of days (or whatever data frequency we are using) we want to simulate prices into the future. Fitting and estimating an asymmetric exponential GARCH (EGARCH) model forms residual returns from the raw return data. By filtering these residual returns they turn independent and identically distributed, and, thereby, become applicable for the scenario building process. Our algorithm therefore also removes serial correlation and volatility clusters if the data contains such structures. Barone Adesi et al. (1999) call their approach semi-parametric since it combines non-parametric historical simulation together with the parametric GARCH model. The standard model used in Barone Adesi et al. (1999) and demonstrated here as our baseline model is the GARCH(1,1) model. Using their notation, with a moving average term, θ, and an autoregressive term, μ, our estimates of the residuals, ϵ_t, and the variance, h_t, are defined as below.

The conditional mean equation can be written as follows:

$$r_t = \mu r_{t-1} + \theta\epsilon_{t-1} + \epsilon_t \qquad \epsilon \sim \mathcal{N}(0, h_t). \tag{2.1}$$

The conditional variance equation can be written as follows:

$$h_t = \omega + \alpha(\epsilon_{t-1} - \gamma)^2 + \beta h_{t-1}. \tag{2.2}$$

The GARCH equation (2.2) specifies the volatility of ϵ_t as a function of ω, a constant, a first term demonstrating the contribution of the latest surprise, ϵ_{t-1}, and a second term reflecting the contribution of the last period's volatility, h_{t-1}. α is a constant and determines the influence of the most recent observation whereas the constant γ determines its asymmetry. We divide the estimated residuals, $\hat{\epsilon_t}$, by the corresponding volatility estimate, $\sqrt{\hat{h_t}}$, to get a stationary i.i.d. distribution, which is suitable for our simulation process,

$$e_t^* = \frac{\hat{\epsilon_t}}{\sqrt{\hat{h_t}}}. \tag{2.3}$$

If the GARCH model is correctly specified the set of standardized residuals, e_t^*, are independent and identically distributed and therefore suitable for historical simulation.[2] This is in contrast to empirical returns, which generally do not fulfill the i.i.d. assumption and therefore are unsuitable for historical simulation.

Randomly drawn historical standardized residuals need to be scaled with the current volatility. Afterward, they can be used in the equations for the conditional mean (2.1) and variance (2.2) to simulate future prices and variances. This random draw is better known as resampling

[2]We provide the empirical test results on the i.i.d. properties, where we use the test of Li and Mak (1994) on the squared residual autocorrelations in nonlinear time series with conditional heteroscedasticity, upon request and publish them in our online appendix.

or bootstrapping, which is what filtered historical simulation essentially does. Randomly, we pick standardized residual returns and use them to generate pathway of variances that themselves are used to build our alternative price path. The randomly drawn standardized residual returns are stored as a vector, $\boldsymbol{e}^*$, of outcomes from the dataset Θ.

$$\boldsymbol{e}^* = \{e_1^*, e_2^*, \ldots, e_T^*\} \qquad \text{where i} = 1, \ldots, T \text{ days.} \tag{2.4}$$

We use the first drawn standardized residual return and scale it using the deterministic volatility forecast for the next day. The deterministic volatility for the next day is constructed as

$$h_{t+1} = \hat{\omega} + \hat{\alpha}(\epsilon_t - \hat{\gamma})^2 + \hat{\beta} h_t. \tag{2.5}$$

The simulated innovation forecast is created by scaling the randomly drawn standardized residual, e_t^*, with the volatility of period $t+1$, h_{t+1}, from Equation (2.5).

$$z_{t+1}^* = e_1^* \sqrt{h_{t+1}}. \tag{2.6}$$

This forecast is used to form the one-day-ahead asset price forecast, p_{t+1}^*, using the asset price at time t, p_t:

$$p_{t+1}^* = p_t + p_t(\hat{\mu} r_t + \hat{\theta} z_t^* + z_{t+1}^*). \tag{2.7}$$

To forecast the volatility for subsequent days ahead we simulate them by recursively substituting the scaled residuals into the variance equation (2.2). Therefore, our first randomly drawn standardized residual from Equation (2.3) enters into the one-day-ahead asset price forecast from Equation (2.7), but is also used for the simulation of the two days ahead volatility forecast. The two-days-ahead volatility is stochastic as it depends on the simulated return of the first day. To simulate the two-days-ahead asset price we randomly pick another standardized residual and scale it. The volatility three days ahead is generated using the previously drawn (second) scaled residual and allows the scaling of the third randomly drawn residual et cetera up until we reach the number of asset price simulations we want to achieve. The volatility simulation takes the following general form:

$$h_{t+i}^* = \hat{\omega} + \hat{\alpha}(z_{t+i-1}^* - \hat{\gamma})^2 + \hat{\beta} h_{t+i-1}^* \qquad i \geq 2. \tag{2.8}$$

The process allows the sequential scaling of randomly drawn standardized residuals to build the asset price pathway. Repeating this process allows us to form various pathways of asset prices. We discuss the underlying methodology for doing so in the following section.

2.2.2 Scenario Building for Multiple Pathways

To simulate multiple pathways, we use the same approach as explained in the previous section. One of the most important aspects when simulating multiple pathways for different assets is how to model the correlation between the assets. In our scenario building process this is done implicitly by randomly drawing a band of residuals as we use the same standardized residual from the same observation for the price and volatility simulation of each asset. We therefore do not need to estimate the correlation matrix. In our multi-asset framework we randomly draw a date from the dataset and pick its corresponding residual returns. These residual returns are used to model the co-movements between the prices of our multi-asset dataset. For each asset in our dataset we have the sampled residuals and denote them with subscripts $1, 2, 3, \ldots, n$ for the different assets.

$$Asset_1 : \boldsymbol{e_1^*} = \{e_1^*, e_2^*, \ldots, e_T^*\}_1. \tag{2.9}$$

$$Asset_2 : \boldsymbol{e_2^*} = \{e_1^*, e_2^*, \ldots, e_T^*\}_2. \tag{2.10}$$

$$Asset_3 : \boldsymbol{e_3^*} = \{e_1^*, e_2^*, \ldots, e_T^*\}_3. \tag{2.11}$$

As in the case for the single pathway, we draw a random date and the associated standardized residuals at day $i = 1$, e_1^* and e_2^* are chosen. At day $i = 2$ another date is randomly drawn together with its associated standardized residuals. This is repeated until we have reached our specified number of daily asset price forecasts. For every asset, the variances, h, and asset prices, p, are modeled such that they reflect the co-movements between each other. For every day $i = 1$ to T we therefore have

$$Asset_1 : h_{1,t+i}^* = \hat{\omega}_1 + \hat{\alpha}_1(\hat{z}_{1,t+i-1}^* - \hat{\gamma})^2 + \hat{\beta}_1 h_{1,t+i-1}^*. \tag{2.12}$$

$$p_{1,t+i}^* = p_{1,t+i-1} + p_{1,t+i-1}(\hat{\mu}_1 r_{1,t+i-1} + \hat{\theta}_1 z_{1,t+i-1}^* + z_{1,t+i}^*). \tag{2.13}$$

$$Asset_2 : h_{2,t+i}^* = \hat{\omega}_2 + \hat{\alpha}_2(\hat{z}_{2,t+i-1}^* - \hat{\gamma})^2 + \hat{\beta}_2 h_{2,t+i-1}^*. \tag{2.14}$$

$$p_{2,t+i}^* = p_{2,t+i-1} + p_{2,t+i-1}(\hat{\mu}_2 r_{2,t+i-1} + \hat{\theta}_2 z_{2,t+i-1}^* + z_{2,t+i}^*). \tag{2.15}$$

$$Asset_3 : h_{3,t+i}^* = \hat{\omega}_3 + \hat{\alpha}_3(\hat{z}_{3,t+i-1}^* - \hat{\gamma})^2 + \hat{\beta}_3 h_{3,t+i-1}^*. \tag{2.16}$$

$$p_{3,t+i}^* = p_{3,t+i-1} + p_{3,t+i-1}(\hat{\mu}_3 r_{3,t+i-1} + \hat{\theta}_3 z_{3,t+i-1}^* + z_{3,t+i}^*). \tag{2.17}$$

2.3 Data & Empirical Results

In this section we present the empirical results of our analysis based on the MSCI World Index with applications on five trading indicators, two of them in the main paper, three in the online appendix. The empirical results for other assets will be generated upon request. The results for the additionally tested assets are collected and documented in our online appendix, together with the backtesting results of other trading indicators.

The simulations are based on the EGARCH(1,1) model; however, the model can be adjusted to fit the data best and the fitting is based on information criteria. Our dataset contains daily price observations from January 2005 to September 2016, which are collected using the Bloomberg Terminal. We calculate the continuous returns of these daily price observations. Our general approach when backtesting the trading strategies is to use either handbook solutions—that is to say, use the calibration proposed when the indicator was originally published, or well-know industry standards. The applied model calibrations generate statistically significant Sharpe ratios when applied to the observed price series. In order to determine the robustness of a trading strategy we apply the same calibration on our set of simulated prices and see how the most important performance metrics behave. Particularly, we focus on outperformance in terms of Sharpe ratio, return, and maximum drawdown relative to the buy-and-hold strategy, but also look at the statistical moments of each respective trading strategy. To not expose ourselves to the data mining claims raised in Bailey et al. 2017; Harvey and Liu 2015; Harvey et al. 2016, we do not optimize the parametrization of the tested trading strategies, however, sensitivity analyses on other calibrations are also possible in this framework.

2.3.1 Simulated Prices

We first report the simulated price series resulting from our scenario building approach. Our full model is based on 20,000 simulated price paths with 2,869 days ahead each—slightly more than 11 years of simulated daily prices per simulated price path. This results in a total of 57.38 million simulated daily data points. In Figure 2.1 we plot a subsample of 50 and in Figure 2.2 a subsample of 2,000 simulated price paths in bluish colors. As described in the theoretical argumentation above, the simulated prices are free to drift away from the observed price series. There are outliers in our price simulations, which are essential for the description of all possible scenarios generated by the statistical data used. To ease the reporting of our results we provide our empirical results by means of charts—if reasonable—and try to avoid large tables. We use the EGARCH(1,1) model for the baseline results reported in this paper, but our approach is flexible to other calibrations or GARCH-type derivatives.

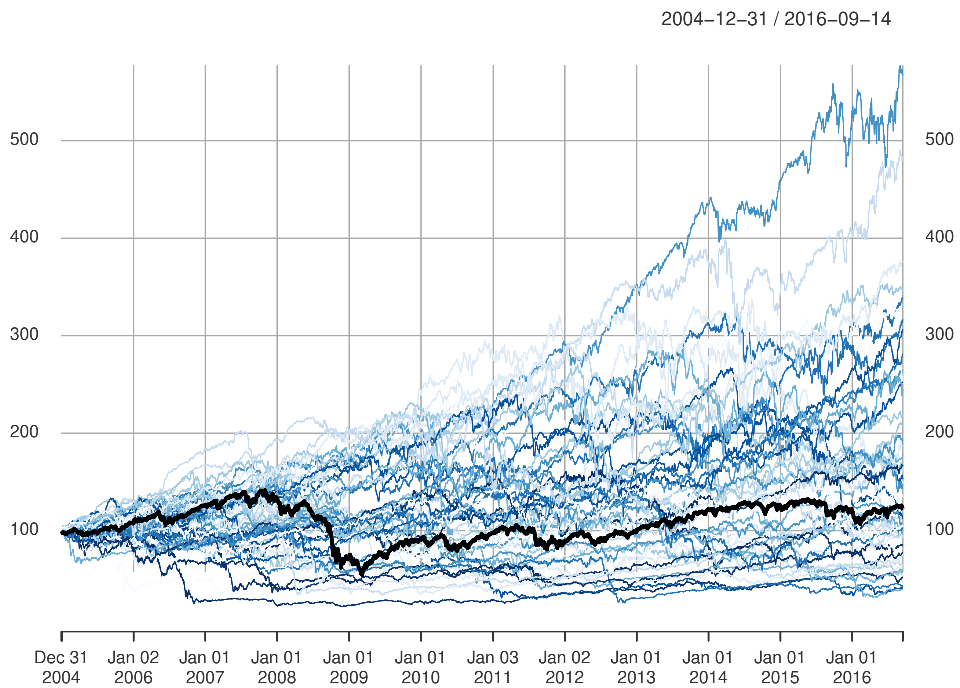


Figure 2.1: This figure shows a subsample of 50 simulated price series in bluish colors, whereas the observed price series is plotted in black.
Source: Based on observed data from the MSCI World Index.

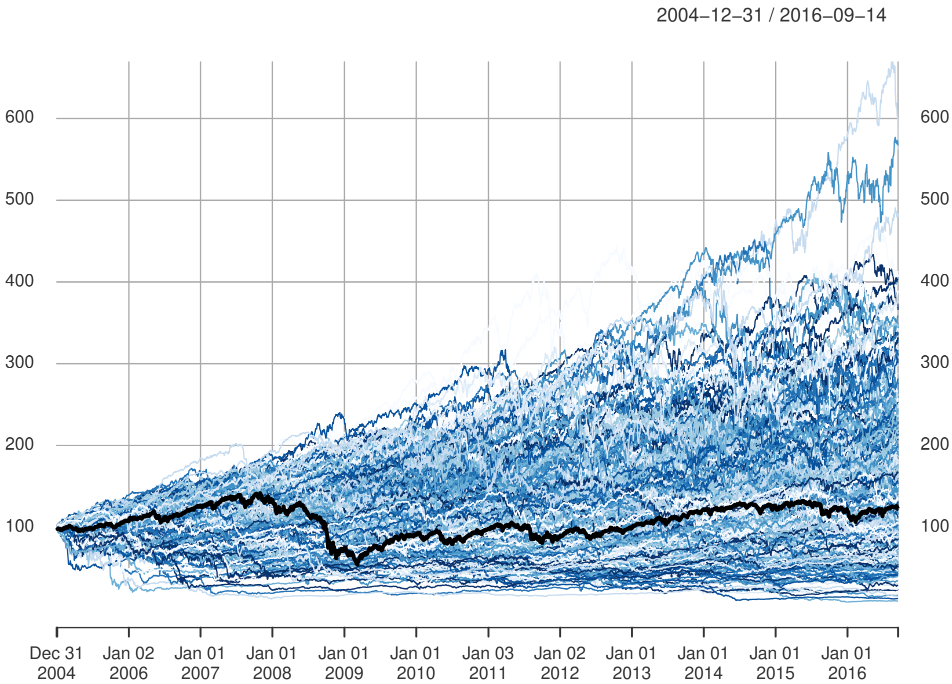


Figure 2.2: This figure shows a subsample of 2,000 simulated price series in bluish colors, whereas the observed price series is plotted in black.
Source: Based on observed data from the MSCI World Index.

2.3.2 Performance Evaluation Methodology

In this section we explain the most important performance metrics used to analyze the performance of our chosen trading strategies. In addition to the excess return, (ER), of each trading strategy, to cover the risk aspect we report the maximum drawdown statistics, (MDD); in the Sharpe ratio (SR) we choose a risk-return metric. On top of these metrics, we also look at statistical moments to see how active trading decisions influence the return distribution.

2.3.2.1 Excess Return

Excess or active return is the part of return that is due to active investment management decisions. To calculate the metric we take the annualized return generated by our active, indicator-based strategy minus the benchmark's annualized return.

$$\mathrm{ER}_k = \mu_k - \mu_{BH}. \tag{2.18}$$

2.3.2.2 Maximum Drawdown

Maximum drawdown is defined as the largest drop from peak to trough over a certain period of time, $[0, T]$. Mathematically speaking, if $v_t(x)$ is the net asset value of a trading strategy at time t, the drawdown function at time t is defined as the difference between the maximum of this function and the value of this function at time t. From the drawdown function, the maximum drawdown can be determined by choosing its maximum value over the entire time interval, $[0, T]$.
Formally, the maximum drawdown of strategy k is defined as

$$\mathrm{MDD}_k = \max_{0 \leq t \leq T} \left(\frac{\max_{0 \leq \tau \leq t}[v_\tau(x)] - v_t(x)}{\max_{0 \leq \tau \leq t}[v_\tau(x)]} \right) \cdot (-1)\,. \tag{2.19}$$

2.3.2.3 Sharpe Ratio

The Sharpe ratio is defined as strategy k's mean of excess returns over the risk-free asset, $\hat{\mu}_k$, divided by its standard deviation, $\hat{\sigma}_k$. Formally, the Sharpe ratio for strategy k is defined as

$$\widehat{\mathrm{SR}}_k = \frac{\hat{\mu}_k}{\hat{\sigma}_k}. \tag{2.20}$$

2.3.2.4 Statistical Moments

Our analysis of statistical moments is focused on how the active trading strategies influence the return distribution. Skewness—the third moment of a statistical distribution—measures the asymmetry of a distribution around its mean, where an asymmetric tail toward positive values results in a positive skewness. Investors typically seek positively skewed return distributions or at least look for less negatively skewed return distributions relative to alternative investment opportunities. Formally, skewness is defined as

$$\text{Skewness} = \frac{1}{n} \cdot \sum_{i=1}^{n} \left(\frac{r_i - \bar{r}}{\sigma_P} \right)^3, \tag{2.21}$$

where n is the number of returns, $\bar{r}$ is the mean of the return distribution, and σ_P is its standard deviation.
The fourth moment, Kurtosis, measures to what degree a distribution is more or less peaked than a normal distribution, where a peaked distribution results in a positive kurtosis. From an investment management perspective, positive kurtosis implies fat tails at the extreme ends of the distribution curve. High kurtosis typically yields overestimation of the probability of achieving the mean return. Formally, kurtosis is defined as

$$\text{Kurtosis} = \frac{1}{n} \cdot \sum_{i=1}^{n} \left(\frac{r_i - \bar{r}}{\sigma_P} \right)^4, \tag{2.22}$$

where n is the number of returns, $\bar{r}$ is the mean of the return distribution, and σ_P is its standard deviation.

2.3.3 Williams %R

The indicator value typically oscillates between 0% and 100%, where 100% implies that the last close price is equal to the high of the range and an indicator value of 0% means that the closing price is equal to the low of the range. The usual application of the Williams %R indicator is with overbought and oversold conditions. Typically, an indicator value of 80% represents the overbought area and if the indicator value is 20%, the underlying security is considered oversold. To calculate the Williams %R indicator we have to deduct the current closing price from the highest price of a specified lookback period. This value has then to be divided by the difference between the highest and the lowest price in our lookback period.

$$\text{Williams \%R}_T = \frac{\max\{P_t, \ldots, P_T\} - Cl(P_T)}{\max\{P_t, \ldots, P_T\} - \min\{P_t, \ldots, P_T\}} \cdot (-1). \tag{2.23}$$

Formally the trading strategy can be formulated as follows:

$$\textit{Long} : \text{Williams \%R}_T \leq x\%, \tag{2.24}$$
$$\textit{Short} : \text{Williams \%R}_T \geq y\%, \tag{2.25}$$

$$0 \leq x \leq y \leq 100.$$

Empirical Results

In our empirical analysis of Williams %R we define 80% as overbought, $y\%$, and 20% as oversold territory, $x\%$. A change in signal is created as soon as the indicator reaches one of these thresholds. The specified lookback period for our empirical testing is 12 days. Therefore our trading strategy can be translated to

$$\textit{Long} : \text{Williams \%R}_{12} \leq 20\%, \tag{2.26}$$
$$\textit{Short} : \text{Williams \%R}_{12} \geq 80\%. \tag{2.27}$$

Distribution of Returns, Maximum Drawdowns, and Sharpe Ratios

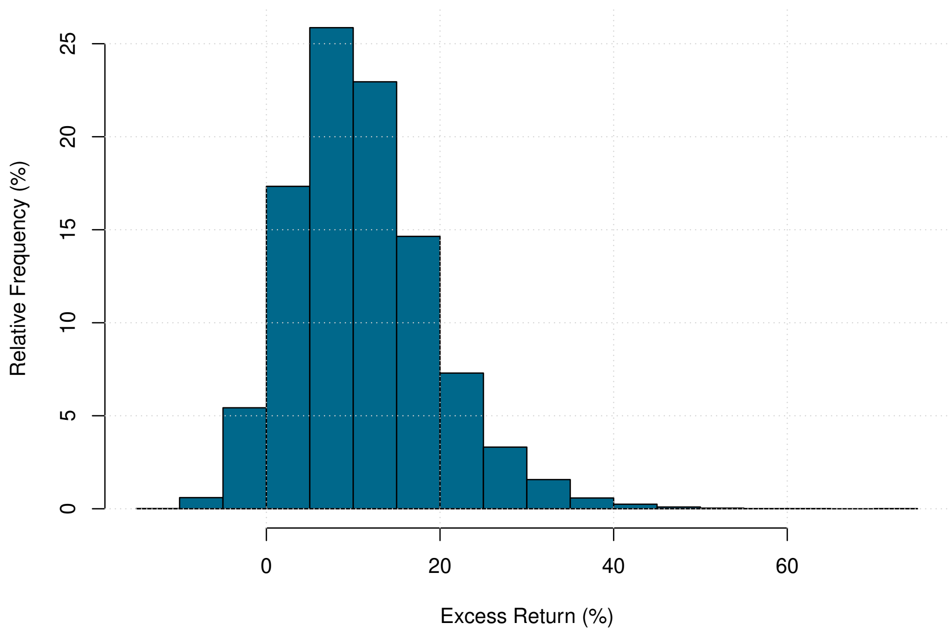


Figure 2.3: This figure shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the Williams %R trading indicator on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 12 days and use 80% as the upper and 20% as the lower signal threshold, respectively. Excess return, as defined in Equation 2.18, is $\mathrm{ER}_k = \mu_k - \mu_{BH}$. We subtract μ_{BH} from μ_k to get the amount by which the active strategy, k, was able to increase the return relative to the passive strategy, *BH*.

Figure 2.3 reports that investing according to the trading signal resulting from the Williams %R indicator—as defined in Equations 2.26 and 2.27—we are able to generate a higher return than by passively holding the asset in almost 95% of our cases. In other words, excess return is negative in slightly more than 5% of our backtests. This is a very strong result and therefore supports the use of Williams %R as a trading indicator. Additionally, figure 2.3 shows that most excess returns are larger than 0% and smaller than 20%, with a peak in the distribution at 5–10% excess return. There are some excess returns on the right end of the distribution that influence the statistical moments of the distribution—an issue we will address later. However, these extreme results are not desirable as it is highly likely that they are only down to luck. Overall, the generated excess returns look desirable. However, we are not seeking higher returns at the cost of higher drawdowns or higher volatility. So the next paragraphs focus on the risk side of this trading strategy by comparing the maximum drawdown of our active strategy relative to that of the buy-and-hold strategy.

The Williams %R also delivers satisfying results for our second performance metric, maximum drawdown. While a small part of our backtests are not able to reduce the maximum drawdown

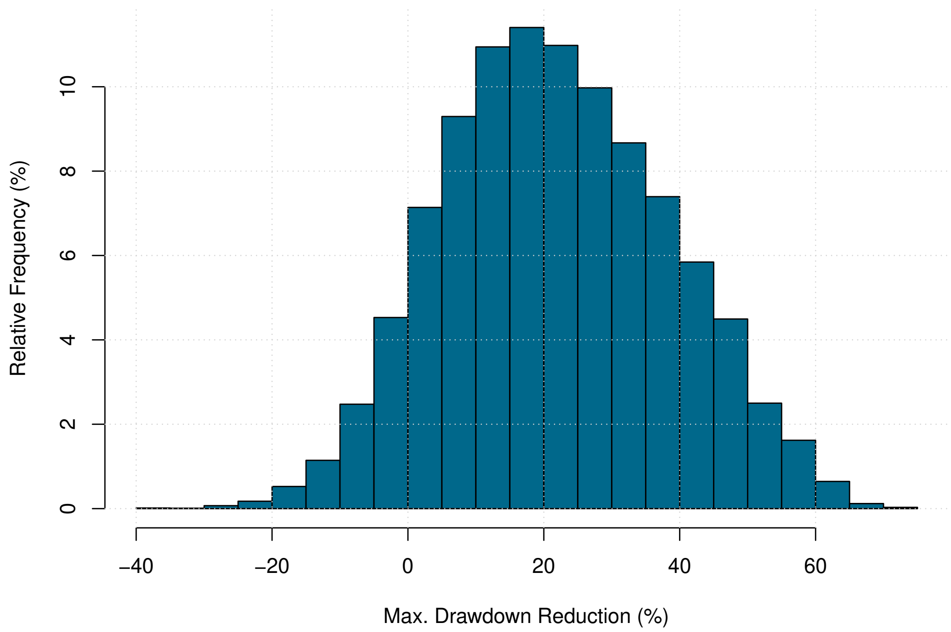


Figure 2.4: This figure shows the maximum drawdown reduction for our empirical backtests based on the MSCI World Index.

Note: We test the Williams %R trading indicator on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 12 days and use 80% as the upper and 20% as the lower signal threshold, respectively. Maximum drawdown, as defined in Equation 2.19, is $\text{MDD}_k = \max_{0 \leq t \leq T} \left(\max_{0 \leq \tau \leq t} [v_t(x)] - v_t(x) \right)$. We subtract MDD_k from MDD_{BH} to get the amount by which the active strategy, k, was able to reduce the maximum drawdown relative to the passive strategy, *BH*.

relative to the buy-and-hold strategy, the largest part do. Remarkable is the fact that the peak in this histogram is in the range of a maximum drawdown reduction of 15–20%, with symmetric distribution in the bins of 10–15 and 20–25%. Therefore, the performance in terms of maximum drawdown reduction is rather stable. As we also observed in the excess return analysis, we have outliers in the right tail, with strikingly good drawdown reduction results.

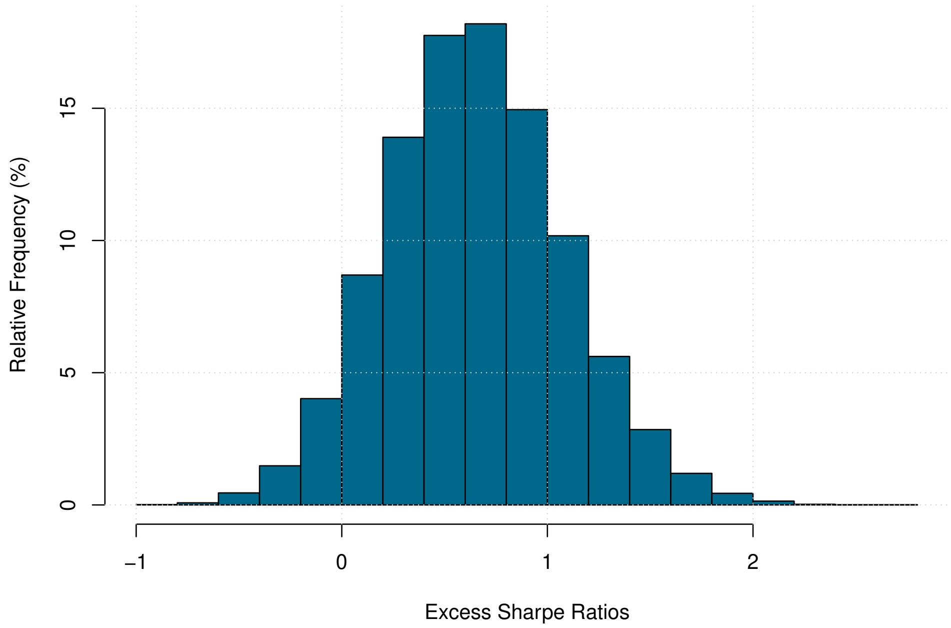


Figure 2.5: This figure shows the excess Sharpe ratios for our empirical backtests based on the MSCI World Index.
Note: We test the Williams %R trading indicator on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 12 days and use 80% as the upper and 20% as the lower signal threshold, respectively. The Sharpe ratio, as defined in Equation 2.20, is $\widehat{\mathrm{SR}}_k = \frac{\hat{\mu}_k}{\hat{\sigma}_k}$. We subtract $\widehat{SR}_{BH}$ from $\widehat{SR}_k$ to get the amount by which the active strategy, k, delivers an improved Sharpe ratio relative to the passive strategy, *BH*.

In terms of excess Sharpe ratio, most observations are positive, therefore outperforming the buy-and-hold strategy. The bin with the highest relative frequency shows an improvement in terms of the Sharpe ratio of between 0.6 and 0.8. Also, we report relatively evenly distributed results with similar outliers in both tails. It is important to note, however, that the distribution is not centered around 0 but, as mentioned earlier, rather around 0.7. Summarizing these three results, the Williams %R delivers satisfying and robust results across the first three performance metrics: excess return, maximum drawdown (reduction), and excess Sharpe ratio. We now continue with the analysis of statistical moments to determine how the trading strategy influences the distribution of returns. Figure 2.6, below, shows the distribution of skewness across all tested price paths. In the first column, labeled *WPR*, we see the summary information for the active strategy, whereas the second column, labeled *BH*, shows it for the passive buy-and-hold strategy. Clearly, following the active trading strategy improves the skewness of the return distribution relative to the benchmark strategy, resulting in a more positively skewed distribution and, thereby, in more positive values. As reported in row seven of Figure 2.6, the skewness of our active strategy is larger than that of the passive buy-and-hold strategy in more than 95% of all backtested cases.

Skewness	WPR	BH
Min. :	-7.057997	-13.60131
1st Qu.:	-0.133179	-0.87940
Median :	0.054186	-0.61466
Mean :	0.128942	-0.73680
3rd Qu.:	0.282069	-0.43446
Max.	11.163594	1.16424
S(WPR) > S(BH):	95.765%	

Figure 2.6: This figure shows the skewness information for the asset MSCI World Index.
Note: The tested indicator is Williams %R, *WPR*; the tested time period ranges from January 2005 to September 2016. Column *BH* reports the results for the buy-and-hold strategy.

Looking at the fourth moment of the return distribution, as reported in Figure 2.7, we see that the kurtosis of our active strategy has only slightly changed relative to the buy-and-hold strategy. In row seven we—again—report how often the kurtosis of our active strategy, *WPR*, is larger than that of the buy-and-hold strategy, *BH*—in 44% of all cases. This result is desirable as we do not necessarily want to introduce fat tails. Overall, we can state that following the Williams %R trading strategy improves the performance metrics mentioned in Subsection 2.3.2 relative to the passive buy-and-hold strategy. The reported results show the necessary robustness and, therefore, support the use of this indicator in our backtests.

Kurtosis	WPR	BH
Min. :	1.3465	1.3505
1st Qu.:	4.4743	4.4888
Median :	6.1950	6.2001
Mean :	8.6268	8.6394
3rd Qu.:	9.2461	9.2430
Max. :	388.0478	388.7687
K(WPR) > K(BH):	44.218%	

Figure 2.7: This figure shows the kurtosis information for the asset MSCI World Index.
Note: The tested indicator is Williams %R, *WPR*; the tested time period ranges from January 2005 to September 2016. Column *BH* reports the results for the buy-and-hold strategy.

2.3.4 Moving Average Cross

The moving average cross is a trend-following trading strategy that has the purpose of identifying the begin of a new or the end of an existing trend. Looking at a moving average plot is similar to using trendlines in technical analysis. As the strategy is a trend-follower, the moving average strategy always has a lagging signal. As the second word of the strategy's name suggests, the moving average cross uses an average of a specific data range. This average price—as the name again implies—moves. In other words, as soon as we have a new observed closing price in our data, we add this to the average calculation and drop the first observation used in the previous average calculation. Therefore, a moving average can be formulated as

$$\mathrm{MA}_{k_1} = \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1}, \tag{2.28}$$

where k_1 = moving average period.

The shorter the moving average period chosen, the closer the filtered series follows the price series. Additionally, a shorter moving average period implies a reduced time lag until the signal is generated. On the other hand, shorter moving average periods are more sensitive to price movements. As the strategy averages the information contained in the price, it has properties comparable to those of econometric filters used in economics and finance (see for example Pedersen 2010) and is therefore used as a smoothing device to filter noise from the data. Formally, the logic of how signals are generated can be stated as follows:

$$\mathit{Long}: \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1} > \sum_{v=-k_2+1}^{0} \frac{P_{t+v}}{k_2}, \tag{2.29}$$

$$\tag{2.30}$$

where $k_{1,2}$ = moving average periods with $0 < k_1 < k_2$.

Empirical Results

In our empirical analysis of the moving average cross strategy we use a short-term oriented trend calibration with a short moving average of five days and a slow moving average of 30 days. For both moving average calculations we use the simple moving average, where each price observation has the same weight.[3] We formally summarize our empirically explored moving average strategy as follows:

$$\mathrm{MA}_5 = \sum_{v=-5+1}^{0} \frac{P_{t+v}}{5}, \tag{2.31}$$

$$\mathrm{MA}_{30} = \sum_{v=-30+1}^{0} \frac{P_{t+v}}{30}, \tag{2.32}$$

[3] The use of exponential (EMA), triangular (TriMA), or volume-weighted (VWAP) moving averages could alternatively be considered.

$$Long : \mathrm{MA}_5 > \mathrm{MA}_{30}. \tag{2.33}$$

(2.34)

Distribution of Returns, Maximum Drawdowns, and Sharpe Ratios

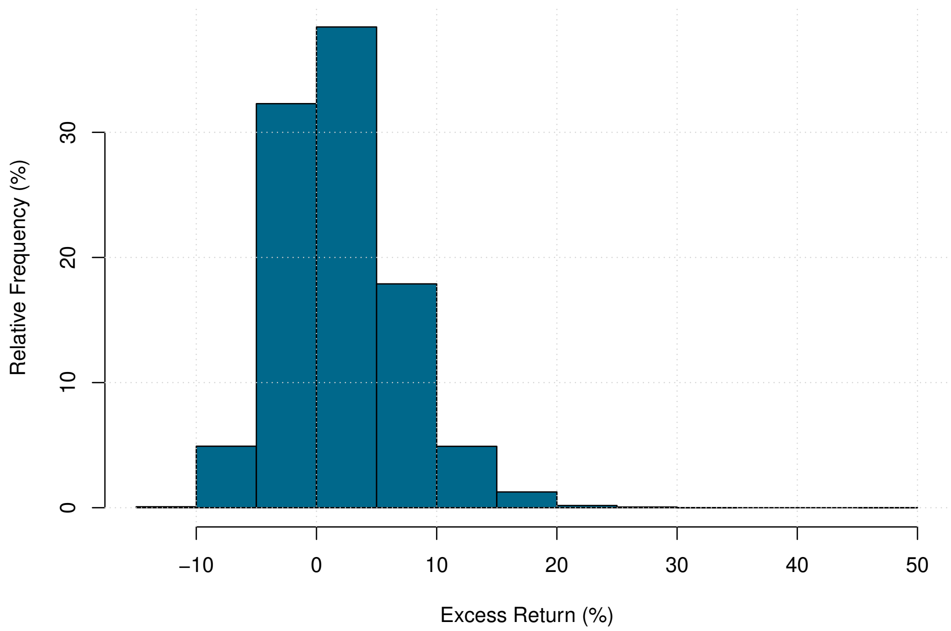


Figure 2.8: This figure shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the moving average cross trading strategy on its robustness by applying it on 20,000 simulated price paths. We use a fast moving average of 5 days and a slow moving average of 30 days. Excess return, as defined in Equation 2.18 is $\mathrm{ER}_k = \mu_k - \mu_{BH}$. We subtract μ_{BH} from μ_k to get the amount by which the active strategy, k, was able to increase the return relative to the passive strategy, *BH*.

The main observation from Figure 2.8 is that excess returns are centered around -5% and +10% with a peak in distribution in the 0–5% bin at a relative frequency of more than 30%, followed by the -5–0% bin. This gives a first indication about the performance of the moving average cross, as the probabilities of improving or worsening, respectively, the return by 5% are each more than 30%. What stands out in a positive way is the fact that the total number of positive bins is larger than the number of negative ones. However, we also observe that many excess return figures are in the right tail with a very low number of observations—which indicates that these results are not too stable. Therefore, in terms of generating excess returns the results are not very promising. Moving to the risk analysis of our backtests, Figure 2.9 shows how the moving average cross strategy is able to reduce the maximum drawdown relative to the buy-and-hold strategy. These results look very appealing, with a peak in distribution in the bins of 10–20% and 20–30%. While this distribution is, therefore, centered around a maximum drawdown reduction of ∼20%, there are close to 5% of observations that lead to a higher maximum drawdown than experienced by following the passive buy-and-hold strategy. On the other hand, the majority of observations show a reduction in maximum drawdown with very few outliers in the right tail—the number of observed outliers is similar in both tails, while the excess return figures in the right tail are almost double in magnitude.

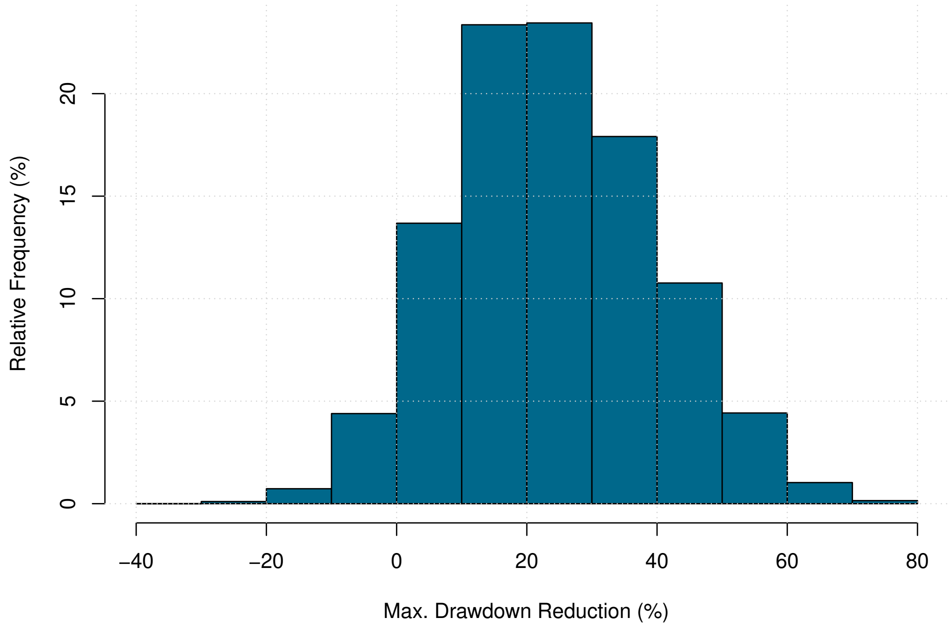


Figure 2.9: This figure shows the maximum drawdown reduction for our empirical backtests based on the MSCI World Index.
Note: We test the moving average cross trading strategy on its robustness by applying it on 20,000 simulated price paths. We use a fast moving average of 5 days and a slow moving average of 30 days. Maximum drawdown, as defined in Equation 2.19, is $\text{MDD}_k = \max_{0 \leq t \leq T} \left(\max_{0 \leq \tau \leq t}[v_t(x)] - v_t(x)\right)$. We subtract MDD_k from MDD_{BH} to get the amount by which the active strategy, k, was able to reduce the maximum drawdown relative to the passive strategy, *BH*.

Figure 2.10 plots the histogram of excess Sharpe ratios, which is almost perfectly symmetrical. The peak of the distribution is located in the bin of Sharpe ratio improvement of 0.0–0.2, followed by that of 0.2–0.4. As the Sharpe ratio is dependent of the (excess) return, these mediocre results are not surprising. On the positive side, we can summarize that the cumulative relative frequency for excess Sharpe ratios is larger than for decreased Sharpe ratios—relative to the passive buy-and-hold strategy. While the majority of observations in this histogram show small but positive values, we can summarize that the strategy generates economically meaningful but statistically insignificantly different results.

While Figure 2.11 shows a less negative minimum and more positive maximum skewness for the active strategy, *MAC*, relative to the benchmark, *BH*, overall the strategy fails to improve

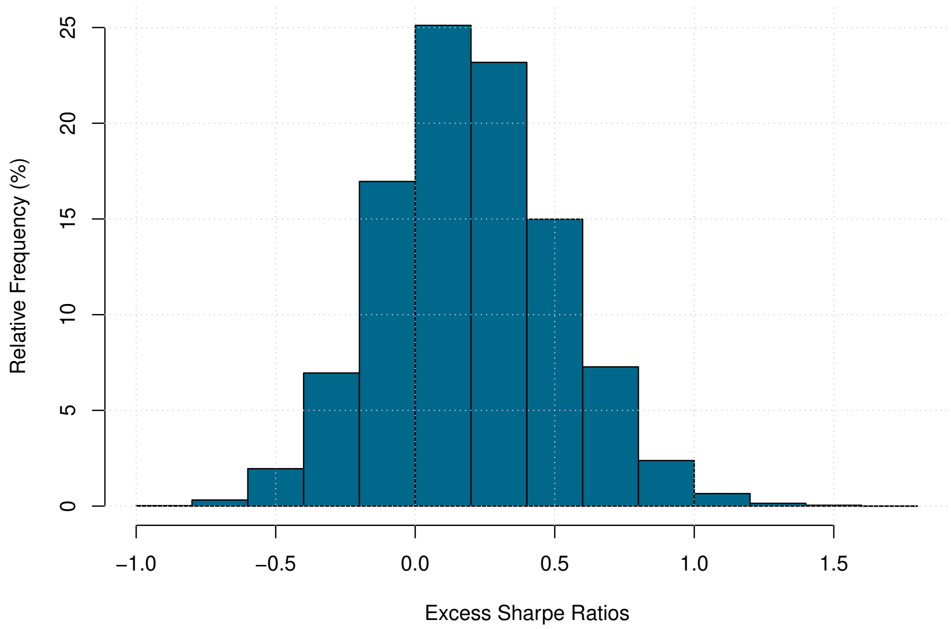


Figure 2.10: This figure shows the excess Sharpe ratios for our empirical backtests based on the MSCI World Index.
Note: We test the moving average cross trading strategy on its robustness by applying it on 20,000 simulated price paths. We use a fast moving average of 5 days and a slow moving average of 30 days. Sharpe ratio, as defined in Equation 2.20, is $\widehat{\mathrm{SR}}_k = \frac{\hat{\mu}_k}{\hat{\sigma}_k}$. We subtract $\widehat{SR}_{BH}$ from $\widehat{SR}_k$ to get the amount by which the active strategy, k, delivers an improved Sharpe ratio relative to the passive strategy, *BH*.

Skewness	MAC	BH
Min. :	-9.48535	-13.60131
1st Qu.:	-0.97131	-0.87940
Median :	-0.66782	-0.61466
Mean :	-0.74938	-0.73680
3rd Qu.:	-0.42126	-0.43446
Max. :	1.89783	1.16424
S(MAC) > S(BH):	44.603%	

Figure 2.11: This figure shows the skewness information for the asset MSCI World Index.
Note: The tested indicator is the moving average cross, *MAC*; the tested time period ranges from January 2005 to September 2016. Column *BH* reports the results for the buy-and-hold strategy.

the skewness. As the outliers in the right tail of Figure 2.8 have already indicated, we also report a higher maximum skewness in *MAC* than in *BH*. Row seven reports how often the skewness of our active strategy was larger than that of the benchmark strategy. Again, this figure is not promising in terms of robustness and performance improvement, as only 44% of all tested strategies have a higher Sharpe ratio than the underlying asset. Strikingly, Figure 2.12 shows that in almost 80% of our backtests the kurtosis of our active strategy is larger than that of its passive counterpart—therefore introducing fatter tails in the return distribution. Apart from the largest kurtosis in all backtests (row six, *Max.*), all summary information shows larger kurtosis for the active strategies, which leads to the aforementioned ∼80%. Overall, the moving average cross strategy does not provide robust results across our backtests. While the results in terms of maximum drawdown reduction and excess Sharpe ratios are satisfying and economically meaningful, the strategy fails to convince in terms of skewness and kurtosis.

Kurtosis	MAC	BH
Min. :	3.1523	1.3505
1st Qu.:	7.3355	4.4888
Median :	9.2310	6.2001
Mean :	11.1830	8.6394
3rd Qu.:	12.2976	9.2430
Max. :	245.5674	388.7687
K(MAC) > K(BH):	79.286%	

Figure 2.12: This figure shows the kurtosis information for the asset MSCI World Index.
Note: The tested indicator is the moving average cross, *MAC*; the tested time period ranges from January 2005 to September 2016. Column *BH* reports the results for the buy-and-hold strategy.

2.4 Additional Results

As mentioned in the introduction to the empirical results in Section 2.3, we do not provide a sensitivity analysis on the tested calibration, as we do not want to expose ourselves to the data mining claims raised in Bailey et al. 2017; Harvey and Liu 2015; Harvey et al. 2016. Instead, we test the calibrations proposed when the indicator was originally published, or well-known industry standards. In addition to the two reported trading indicators in the main paper, we test three additional indicators, namely: the relative strength index (RSI), the Chande momentum oscillator (CMO), and the commodity channel index (CMO). The RSI shows interesting properties in terms of risk-reduction, when we compare the indicator's outperformance versus the buy-and-hold strategy in terms of maximum drawdown. On the other hand, from a return oriented perspective, the indicator is not convincing. The Chande momentum oscillator shows poor properties in all reported performance metrics. Especially the inability to generate positive excess returns versus the passive benchmark strategy is disappointing. This finding is also reflected in the poor performance in terms of generating excess Sharpe ratio. As is true for the relative strength index, the CMO performs strongly form a risk perspective. The most convincing tested indicator is the commodity channel index, which shows robust and positive excess returns with heavy right tails. While the maximum drawdown figures also show relatively stable outperformance versus the benchmark strategy, the excess return is also reflected in excess Sharpe ratio, which has only around 10% of negative observations. On top, the distribution of excess Sharpe ratio for CCI is clustered around 0.4–0.8 with a relative frequency of around 15% for each bar.

2.5 Conclusion

In this paper we simulate alternative price paths based on the observed, empirical distribution of past returns. This allows us to circumvent the problem of pre-specifying a distribution function that our simulated returns have to follow. Our scenario building model is able to generate artificial price paths for a specific asset or multiple assets, which then can be used to test trading strategies on their robustness. Using our scenario building approach, we generate 20,000 simulated price paths, each of them consisting of 2,869 days, therefore totaling 57.38 million simulated daily data points. Typically, trading strategies are tested on robustness using one of two approaches. Pro forma out-of-sample tests are applied, using a part of the sample to fit the strategy and another part of the sample, which was kept outside of the fitting process, to verify the strategy. Alternatively, price series of other assets are used. This, however, can yield the strategy's developer rejecting a reasonable trading strategy since it does not perform equally well on both assets.

With this paper, we provide a framework with which to backtest trading strategies and show an application using the technical trading rules Williams %R and the moving average cross. Keeping the strategy configuration identical for every backtest, we find that the Williams %R indicator is able to deliver mostly positive and stable excess returns and Sharpe ratios for almost every scenario. In terms of risk, the strategy has a sound distribution of maximum drawdown reduction, with heavy right tails. The statistical moments of the return distribution reported for the Williams %R strategy are also favorable: While it drastically reduces the minimum skewness across the backtesting sample, the mean and median skewness are increased, implying higher average returns. The results for kurtosis show that Williams %R does slightly change the distribution relative to the underlying's asset returns; it does not, however, badly influenced it—especially in combination with the increased skewness. The moving average cross strategy, on the other hand, fails to constantly deliver positive excess returns, with most excess return observations around ±5%. It does, however, deliver surprisingly good and stable results in terms of maximum drawdown reduction. The unsatisfying excess return results are also partly reflected in the excess Sharpe ratio results; they are economically meaningful but the improvement in terms of Sharpe ratio are quite small. While the moving average cross strategy reduces the lowest observed skewness reported relative to the buy-and-hold strategy, it is not able to significantly improve the mean and median skewness figures. Also, the strategy impacts the fourth moment strongly, increasing the kurtosis of the return distribution in 80% of all backtests. The combination of these findings for the moving average cross strategy are not fully satisfying and do not provide evidence of stable performance.

Concluding, this paper provides quantitative developers a backtesting environment in which to put their trading strategies to the test and to see how robust their strategies and chosen parametrizations are. As the presented scenario building process can be used to simulate multiple assets from different asset classes, there are almost no limits with respect to which trading strategies are testable. To name but a few, trading strategies ranging from technical analysis, through cross-sectional momentum strategies based on multiple assets—such as described in Jegadeesh and Titman (1993)—to pair-trading approaches can be tested on their performance robustness within this framework. From a computational perspective, the parallel bootstrapping process implicitly handles the cross dependencies among the data series. Our simulation process therefore reduces the complexity of the task enormously as the number of parameters and the time needed to execute the computation increase only linearly with the number of assets that are handled (see Barone Adesi et al. (1999)). This is different to approaches that model cross dependencies based on estimates of the variance–covariance matrix, where the dimension of the problem increases quadratically with the number of assets.

Acknowledgments

I would like to thank my advisor Karl Schmedders for his support and guidance in this project. I would also like to thank Malte Schumacher for his feedback, and the conference audience at the 2017 World Finance Conference, especially Charikleia Kaffe for her extensive review.

B Appendix: Chapter 2

B.1 Additional Trading Indicators

This appendix reports backtesting results for additional trading indicators, namely:

1. Relative Strength Index (RSI)
2. Chande Momentum Oscillator (CMO)
3. Commodity Channel Index (CCI)

B.1.1 Relative Strength Index

As a momentum oscillator, the relative strength index, RSI, expresses the change and speed of price movements by calculating the ratio between the recent upward price movements and the absolute price movement. To calculate the oscillator, we first need to specify a lookback period, n—following Wilder (1978), we set it to 14 days. As already stated in the main paper, shorter lookback periods result in more sensitive oscillators. Traditionally, the indicator oscillates in the range between zero and 100. Typically, the relative strength indicator is used with oversold and overbought conditions—that is to say, one shorts an asset once it is in the overbought area and one buys an asset once it is in the oversold area.
The formula for calculating the RSI is defined in Wilder (1978) as

$$\mathrm{RSI}_n = 100 - \left(\frac{100}{1+\mathrm{RS}}\right), \tag{B.1}$$

$$\text{where RS} = \frac{\sum_{n=1}^{N} \frac{U}{n}}{\sum_{n=1}^{N} \frac{D}{n}}, \tag{B.2}$$

$$\text{with U} = (P_t - P_{t-1}) \text{ for } P_t > P_{t-1} \tag{B.3}$$

$$\text{and D} = (P_{t-1} - P_t) \text{ for } P_t < P_{t-1}. \tag{B.4}$$

Formally the trading strategy can be formulated as follows:

$$Long : \mathrm{RSI}_n \leq x, \tag{B.5}$$

$$Short : \mathrm{RSI}_n \geq y,$$

$$\text{with } 0 \leq x \leq y \leq 100.$$

Empirical Results

Our empirical analysis of the relative strength index is based on a lookback period of 14 days. Over this period, we smooth the oscillator using an equally weighted, simple moving average. A long signal is generated once the indicator reaches a value, x, of 30. The upper threshold, y, is 70, which triggers a short position in our trading strategy. We formally summarize our empirically explored relative strength index strategy as follows:

$$Long : \mathrm{RSI}_{14} \leq 30, \tag{B.6}$$

$$Short : \mathrm{RSI}_{14} \geq 70. \tag{B.7}$$

Distribution of Returns, Maximum Drawdowns, and Sharpe Ratios
Figure B.1 shows the excess return for the relative strength index, *RSI*. With over 70% of all returns, the largest part of the distribution is in the negative territory, with a peak of the distribution between -5–0%. Disappointingly, also the second largest relative frequency is negative, from -5–10%. Only slightly more than 20% of all the reported excess returns are in the positive territory of the return distribution. Also, we detect observations far out in the tails of the excess return distribution. Overall, these results do not support a positive, robust performance in terms of excess return. The maximum drawdown reduction in Figure B.2 looks much more promising with a largest number of observations in terms of maximum drawdown reduction observed in the distribution peak between 0–10%. While the two bins with the highest relative frequency are reductions of maximum drawdowns in the range of 0–20%. Also, we have almost symmetric bins on the left and right side of the bin with the largest number of observations in the -10–0% bin on the left and the 10–20% bin on the right—both with a relative frequency of around 20%. Again, we have some observations in the tails, but the majority of returns can be described with the above mentioned bins. The poor excess return properties reported above and displayed in Figure B.1, are also represented in Figure B.3, which shows the generated excess Sharpe ratio. As the excess return is an input factor of excess Sharpe ratio calculations, these figures are also disappointing. Almost 90% of all observations are negative, meaning that only 10% of all backtested strategies outperform the buy-and-hold strategy in terms of Sharpe ratio. Additionally, the $\sim$10% that are able to generate a higher Sharpe ratio than the buy-and-hold strategy, do this on a very low level. Looking at the statistical moments of the distribution, we see in Figure B.4 how the active strategy influences the skewness of the return distribution. Clearly, the relative strength index does not improve the skewness relative to its benchmark strategy, *BH*. While the largest skewness is detected in an RSI-based strategy, overall, only 33% of all RSI-based strategies experience a higher skewness than their passive counterpart. On the other hand, following the signals generated by the relative strength index increases the kurtosis significantly, as reported in Figure B.5. Hence, 99.96% of all backtested RSI-strategies experience higher kurtosis than observed in the passive buy-and-hold strategy. Summarizing our findings, we can state, that the relative strength index is not able to generate robust return-related performances. From a risk-based perspective, the RSI shows promising results, reducing the maximum drawdown figures significantly for a large number of observations. Nonetheless—

overall—the strategy fails to fully convince in terms of the other reported performance metrics. As a side-note, we have to mention, that the relative strength index is usually not used as a standalone trading indicator but rather in combination with other trend indicators, as markets can technically be overbought or -sold for a long time.

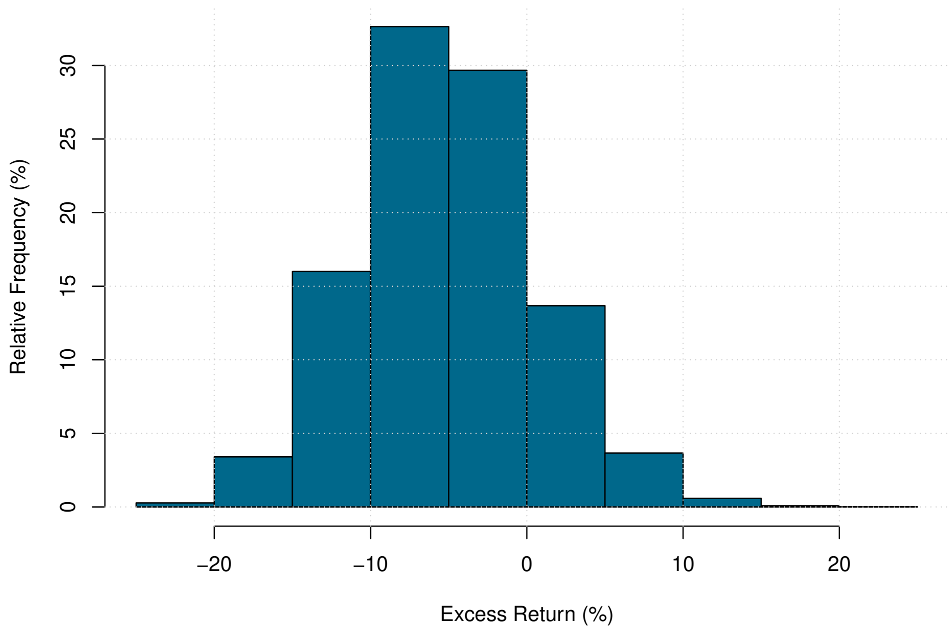


Figure B.1: This chart shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the relative strength index on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 20 days and use 70% as the upper and 30% as the lower signal threshold, respectively. Excess return, as defined in Equation 2.18, is $\mathrm{ER}_k = \mu_k - \mu_{BH}$. We subtract μ_{BH} from μ_k to get the amount by which the active strategy, k, was able to increase the return relative to the passive strategy, *BH*.

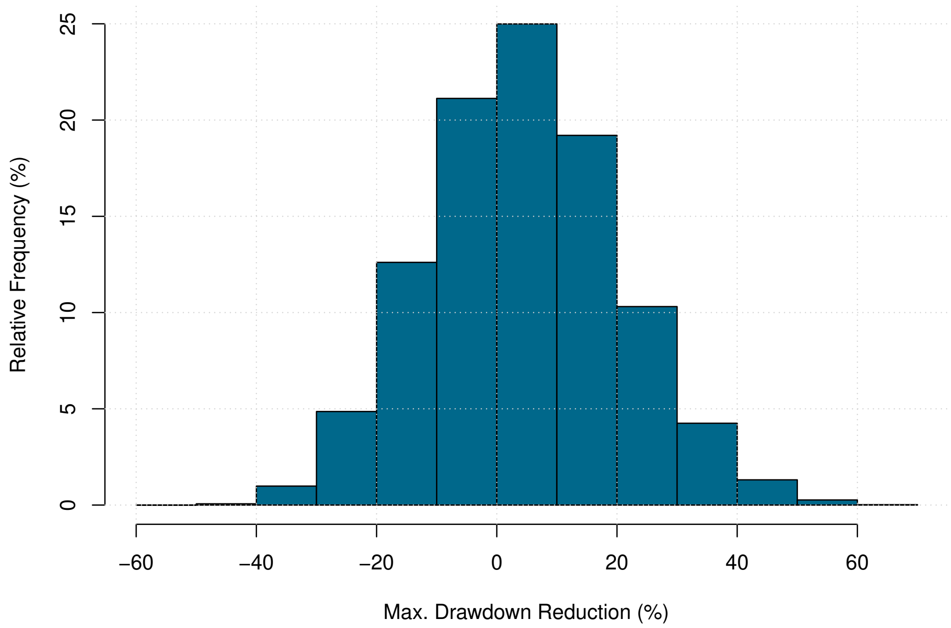


Figure B.2: This chart shows the maximum drawdown reduction for our empirical backtests based on the MSCI World Index.
Note: We test the relative strength index on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 20 days and use 70% as the upper and 30% as the lower signal threshold, respectively. Maximum drawdown, as defined in Equation 2.19, is $\mathrm{MDD}_k = \max_{0\leq t\leq T}\left(\max_{0\leq\tau\leq t}[v_t(x)] - v_t(x)\right)$. We subtract MDD_k from MDD_{BH} to get the amount by which the active strategy, k, was able to reduce the maximum drawdown relative to the passive strategy, *BH*.

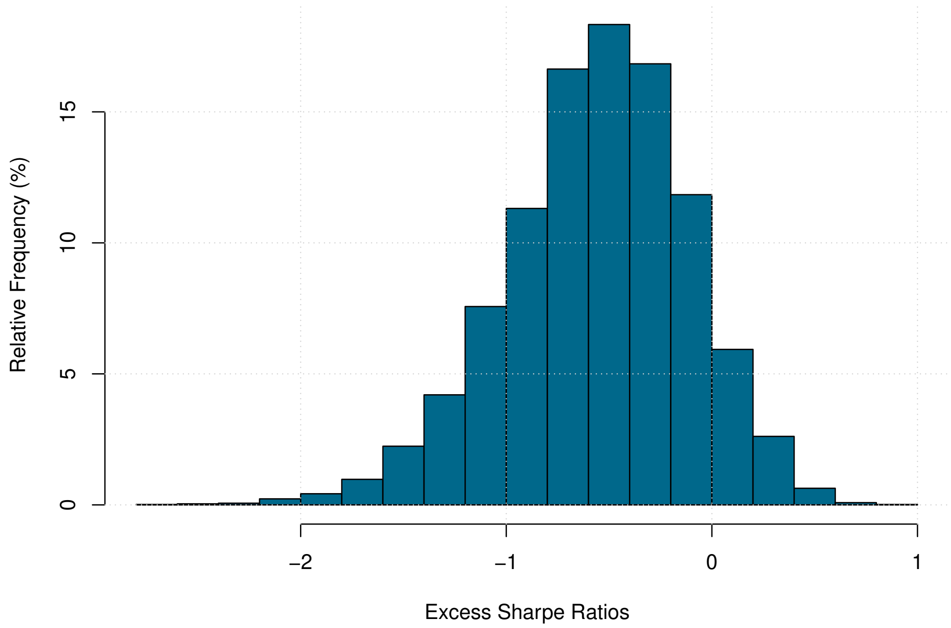


Figure B.3: This chart shows the excess Sharpe ratio for our empirical backtests based on the MSCI World Index.
Note: We test the relative strength index on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 20 days and use 70% as the upper and 30% as the lower signal threshold, respectively. The Sharpe ratio, as defined in Equation 2.20, is $\widehat{\mathrm{SR}}_k = \frac{\hat{\mu}_k}{\hat{\sigma}_k}$. We subtract $\widehat{SR}_{BH}$ from $\widehat{SR}_k$ to get the amount by which the active strategy, k, delivers an improved Sharpe ratio relative to the passive strategy, *BH*.

Skewness	RSI	BH
Min. :	-24.90720	-13.60131
1st Qu.:	-2.24289	-0.87940
Median :	-1.14354	-0.61466
Mean	: -1.39527	-0.73680
3rd Qu.:	-0.22568	-0.43446
Max. :	9.21977	1.16424
S(RSI) > S(BH):	33.108%	

Figure B.4: This figure shows the skewness information for the asset MSCI World Index.
Note: The tested indicator is the relative strength index, RSI; the tested time period ranges from January 2005 to September 2016. Column *BH* reports the results for the buy-and-hold strategy.

Kurtosis	RSI	BH
Min. :	14.507	1.3505
1st Qu.:	33.584	4.4888
Median :	43.703	6.2001
Mean :	55.003	8.6394
3rd Qu.:	61.079	9.2430
Max. :	1017.929	388.7687
K(RSI) > K(BH):	99.955%	

Figure B.5: This figure shows the kurtosis information for the asset MSCI World Index.
Note: The tested indicator is the relative strength index, RSI; the tested time period ranges from January 2005 to September 2016. Column BH reports the results for the buy-and-hold strategy.

B.1.2 Chande Momentum Oscillator

Published in Chande and Kroll (1994), the Chande momentum oscillator, CMO, is similar to the RSI we presented in Section B.1.1. To explain the differences, we start with the formal definition of the indicator, before cross-comparing it with the RSI.

$$\mathrm{CMO}_n = 100 \times \frac{\sum_{n=1}^{N} U - \sum_{n=1}^{N} D}{\sum_{n=1}^{N} U + \sum_{n=1}^{N} D}, \tag{B.8}$$

with U and D as defined above in Equations B.3, and B.4, respectively.
The Chande momentum oscillator is therefore different from the relative strength index as we divide the total movement by the net movement, whereas for the relative strength index we divide the upward movement by the net movement.
Formally, the trading strategy can be formulated as follows

$$\mathit{Long} : \mathrm{CMO}_n \leq x, \tag{B.9}$$

$$\mathit{Short} : \mathrm{CMO}_n \geq y,$$

$$-100 \leq x \leq y \leq 100.$$

Unlike for the RSI, the calculations for the CMO are based on unsmoothed data—meaning major short-term movements are visible and not concealed. As a consequence, the indicator reaches overbought and oversold conditions faster and more often. The indicator value oscillates in the range of ± 100 with value of zero representing the neutral level between periods of either positive or negative momentum.

Empirical Results

We calculate the Chande momentum oscillator based on a lookback period of 12 days. As mentioned above, in contrast to the RSI, the CMO series is not smoothed, resulting in less smooth signal function. A long signal is generated once the indicator reaches a value, x, of -50. The upper threshold, y, is 50, which triggers a short position in our trading system. We formally summarize our empirically explored moving average strategy as follows

$$\mathit{Long} : \mathrm{CMO}_{12} \leq -50, \tag{B.10}$$

$$\mathit{Short} : \mathrm{CMO}_{12} \geq 50. \tag{B.11}$$

Distribution of Returns, Maximum Drawdowns, and Sharpe Ratios
The excess return distribution resulting from the Chande momentum oscillator plotted in Figure B.6 shows a nearly symmetric distribution. Unfortunately, the distribution is centered around -5%, with the highest relative frequency between -5–0%. The second most often observed excess returns fall in the range of -10–-5%. With both bins individually counting for more than 30% of the relative frequency, we have an additional bin of -15–-10% with a relative frequency of almost 15%, and a smaller bin from -20–-15% with a frequency of less than 5%. On the positive side of excess returns, we have the 0–5% bin with a relative frequency of slightly more than 15%, and a bin of 5–10% with a frequency of 5%. Clearly, these results are not satisfying in terms of excess return generation, as the benchmark strategy performs better in almost 80% of all backtests run. From a drawdown perspective, our backtesting results look much better, as reported in Figure B.7. Considerably more than 60% of the relative frequency are positive values, implying a reduced maximum drawdown relative to the buy-and-hold strategy, with the highest number of observation in the bin with a maximum drawdown reduction of 0–10%, followed by a reduction of 10–20%. However, more than 15% fall in the -5–0% bin, which detracts slightly. Overall, we can say that the Chande momentum oscillator does a fairly good job in reducing the experienced maximum drawdowns. What holds true for every tested indicator that reports bad result in terms of excess return is also true for the Chande momentum oscillator: it is reflected in the excess Sharpe ratios. Remarkably, only $\sim$10% of the reported excess Sharpe ratios are positive. Figure B.9 also reflects the adverse effects this trading strategy has on the distribution of the return distribution, as the skewness is much more negative, i.e. having more observations in the left tail of the distribution. Across all tested series, only one third of all strategies generate a skewness which is larger than the benchmark's skewness. Interpreting the results of the fourth moment of the return distribution speaks also clearly against the Chande momentum indicator, as the kurtosis is larger than the kurtosis of the benchmark strategy in more than 99% of the tested cases, as reported in Figure B.10. Therefore, the combination of higher kurtosis and more observations in the left tail of the distribution—fat tails—is not desirable. Overall, this strategy does not deliver promising results in terms of performance robustness and properties.

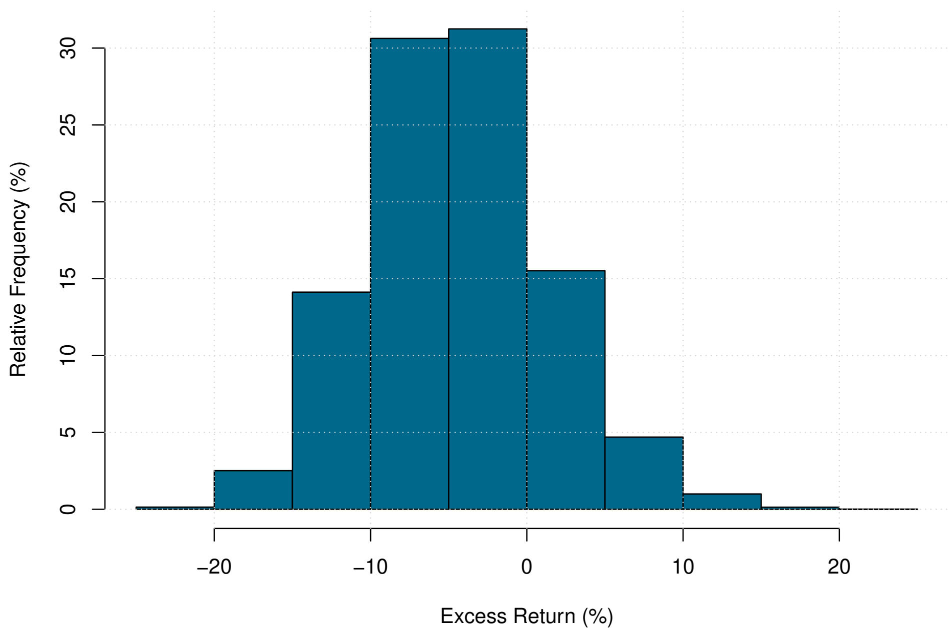


Figure B.6: This chart shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the Chande momentum oscillator on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 12 days and use 50 as the upper and -50 as the lower signal threshold, respectively. Excess return, as defined in Equation 2.18, is $\text{ER}_k = \mu_k - \mu_{BH}$. We subtract μ_{BH} from μ_k to get the amount by which the active strategy, k, was able to increase the return relative to the passive strategy, *BH*.

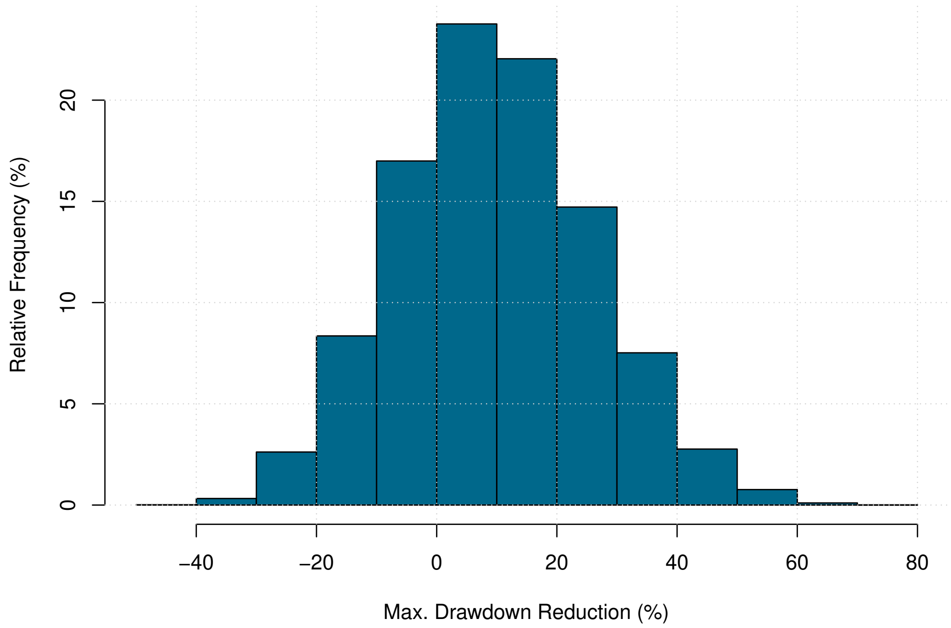


Figure B.7: This chart shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the Chande momentum oscillator on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 12 days and use 50 as the upper and -50 as the lower signal threshold, respectively. Maximum drawdown, as defined in Equation 2.19, is $\mathrm{MDD}_k = \max_{0\leq t\leq T}\left(\max_{0\leq\tau\leq t}[v_t(x)] - v_t(x)\right)$. We subtract MDD_k from MDD_{BH} to get the amount by which the active strategy, k, was able to reduce the maximum drawdown relative to the passive strategy, *BH*.

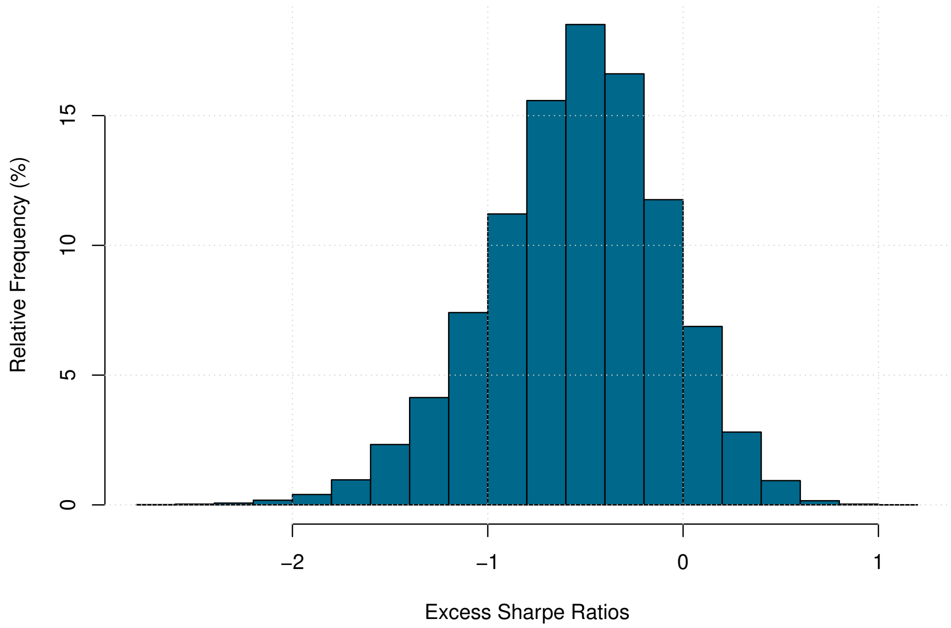


Figure B.8: This chart shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the Chande momentum oscillator on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 12 days and use 50 as the upper and -50 as the lower signal threshold, respectively. The Sharpe ratio, as defined in Equation 2.20, is $\widehat{\mathrm{SR}}_k = \frac{\hat{\mu}_k}{\hat{\sigma}_k}$. We subtract $\widehat{SR}_{BH}$ from $\widehat{SR}_k$ to get the amount by which the active strategy, k, delivers an improved Sharpe ratio relative to the passive strategy, *BH*.

Skewness	CMO	BH
Min. :	-29.34107	-13.60131
1st Qu.:	-2.10567	-0.87940
Median :	-1.07458	-0.61466
Mean :	-1.34714	-0.73680
3rd Qu.:	-0.22834	-0.43446
Max. :	8.73613	1.16424
S(CMO) > S(BH):	34.228%	

Figure B.9: This figure shows the skewness information for the asset MSCI World Index.
Note: The tested indicator is the Chande momentum oscillator, *CMO*; the tested time period ranges from January 2005 to September 2016. Column *BH* reports the results for the buy-and-hold strategy.

Kurtosis	CMO	BH
Min. :	14.474	1.3505
1st Qu.:	30.022	4.4888
Median :	39.040	6.2001
Mean :	50.661	8.6394
3rd Qu.:	55.676	9.2430
Max. :	1321.029	388.7687
K(CMO) > K(BH):	99.865%	

Figure B.10: This figure shows the kurtosis information for the asset MSCI World Index.
Note: The tested indicator is the Chande momentum oscillator, CMO; the tested time period ranges from January 2005 to September 2016. Column BH reports the results for the buy-and-hold strategy.

B.1.3 Commodity Channel Index

The commodity channel index, CCI, intends to identify when trends start or end. It relates today's price to the average price over k_1 periods. As for the other indicators presented above, the CCI can be used to identify oversold and overbought conditions.

$$\mathrm{CCI}_k = \frac{(P_t - \sum_{v=-k_1+1}^{0} \frac{P_{t+v}}{k_1})}{c \times MAD}, \tag{B.12}$$

$$\text{where } k_1 = \text{moving average period,}$$

$$c = \text{is a scaling constant, and}$$

$$MAD = \text{mean absolute deviation.}$$

In his original paper, Lambert (1980) set the scaling constant, c, at 1.5% as to assure that approximately 75% of the values fall into the range of ±100, which is defined as "trendless" range in Lambert (1980). The most basic implementation of the commodity channel index is—in analogy to the oscillators presented above—go long if the indicator value rises above 100 and go short when it falls below -100.

The empirically explored example is based on a lookback period of 20 days. This lookback period, n, of 20 days is also used for the moving average and mean deviation.
Formally the trading strategy can be formulated as follows

$$Long : \mathrm{CCI}_k \geq y\%, \tag{B.13}$$

$$Short : \mathrm{CCI}_k \leq x\%,$$

Empirical Results

We calculate the commodity channel index based on a lookback period of 20 days. As for the RSI, we apply an equally weighted smoothing filter on the signal series. A long signal is generated once the indicator reaches a value, x, of -100. The upper threshold, y, is 100 and triggers a short position in our trading strategy. The constant is set to 0.015, as defined in the original paper. We formally summarize our empirically explored moving average strategy as follows:

$$Long : \mathrm{CCI}_{20} \geq 100, \tag{B.14}$$

$$Short : \mathrm{CCI}_{20} \leq -100, \tag{B.15}$$

$$\mathrm{c} = \text{set to } 1.5\%. \tag{B.16}$$

Distribution of Returns, Maximum Drawdowns, and Sharpe Ratios

Figure B.11 plots the excess returns generated by following the commodity channel index compared to the passive buy-and-hold strategy. More than 20% of all excess return observations are in the bin of 0–5% and another 20% are in the 5–10% bin. The bin with the third largest relative frequency is the 10–15% bin—and these three largest bins together already add up to more than 60% of all observations. On the negative side, we observe close to 15% of excess returns in the -5–0% bin. While this -5–0% bin still contains a large percentage, three quarters of all observations are positive, which seems to be a promising result. Obviously, the trading strategy introduces extreme return observations into the right tail of the distribution. In Figure B.12 we report the maximum drawdown reduction of our active strategy, *CCI*, relative to the passive strategy. First, we clearly observe that fewer than 400 observations lead to a higher maximum drawdown relative to the benchmark strategy—which translates into a less than 2% relative frequency. Second, we have a peak in distribution in the two bins 30–35% and 25–30% maximum drawdown reduction. Overall, the histogram shows evenly distributed results, however with low relative frequencies. The positive aspect of these low relative frequencies—around 10% each—is that maximum drawdown reduction in the range of 20–40% has a probability of around 40%. Plotting the histogram of excess Sharpe ratios in Figure B.13 reveals that less than 10% of all backtested active strategies have a Sharpe ratio smaller than the benchmark's Sharpe ratio. Also, this implies that 90% of all backtested active trading strategies outperform their passive benchmark in terms of Sharpe ratio. Additionally, we have a peak in the bin of 0.6–0.8%, followed by 0.4–0.6% and 0.8–1%—all of which are reported with a relative frequency of around 15%. As these results look promising in terms of performance and its robustness, we dig deeper in Figure B.14 where we look at the skewness of our backtested strategies. The summary statistics clearly show the improvement in terms of skewness, reporting a median of 0.83 and mean of 1.05 for the active strategies compared to the median of -0.61 and mean of -0.74 of the passive strategies. In row seven of Figure B.14 we report that 96.17% of all backtested strategies based on the commodity channel index have a higher skewness than their passive benchmark, therefore improving the return profile from an investor's point of view. This fact is also visible in row seven of Figure B.15, where we report that 99.58% of our commodity channel index based strategies experience a higher kurtosis than the passive benchmark strategies. While higher kurtosis is not per se good or bad from an investor's perspective, this is a nice property combined with the aforementioned results in Figure B.14 where we discussed the skewness of these backtests. Overall, the backtesting results using the commodity channel index to generate trading signals are convincing across all performance metrics.

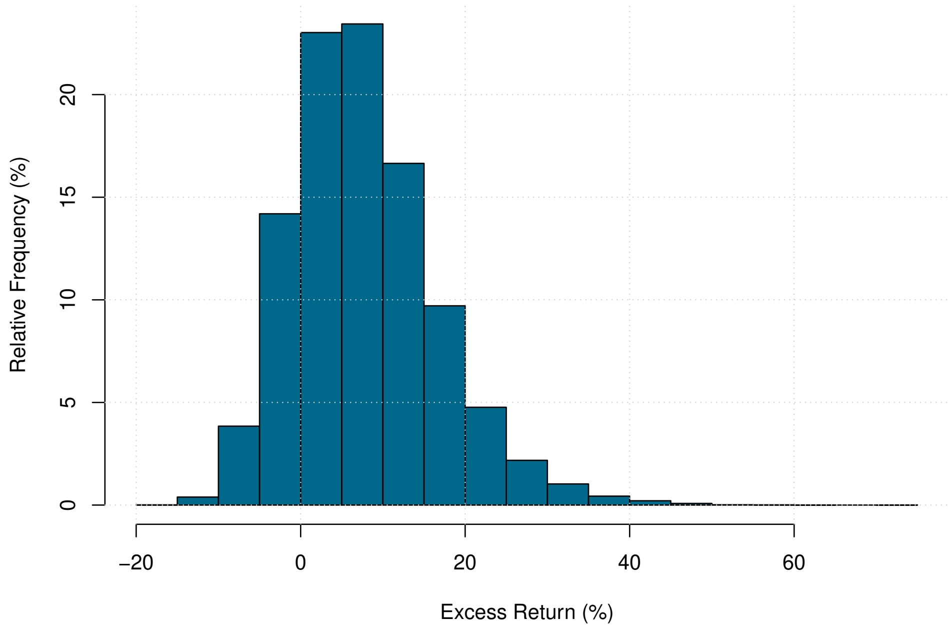


Figure B.11: This chart shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the commodity channel index on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 20 days and use 100 as the upper and -100 as the lower signal threshold, respectively. Excess return, as defined in Equation 2.18, is $\text{ER}_k = \mu_k - \mu_{BH}$. We subtract μ_{BH} from μ_k to get the amount by which the active strategy, k, was able to increase the return relative to the passive strategy, *BH*.

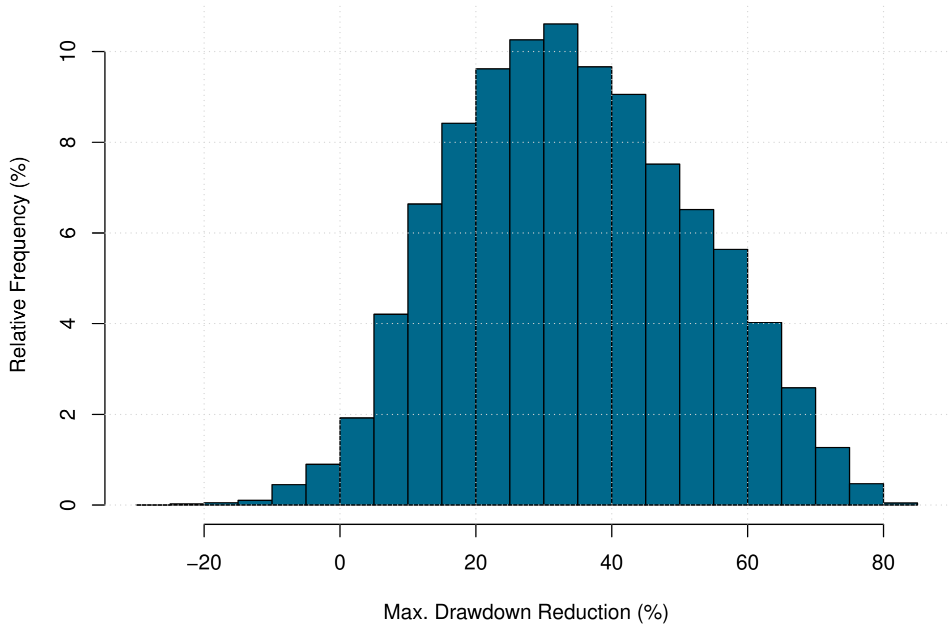


Figure B.12: This chart shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the commodity channel index on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 20 days and use 100 as the upper and -100 as the lower signal threshold, respectively. Maximum drawdown, as defined in Equation 2.19, is $\mathrm{MDD}_k = \max_{0\leq t\leq T}\left(\max_{0\leq\tau\leq t}[v_t(x)] - v_t(x)\right)$. We subtract MDD_k from MDD_{BH} to get the amount by which the active strategy, k, was able to reduce the maximum drawdown relative to the passive strategy, *BH*.

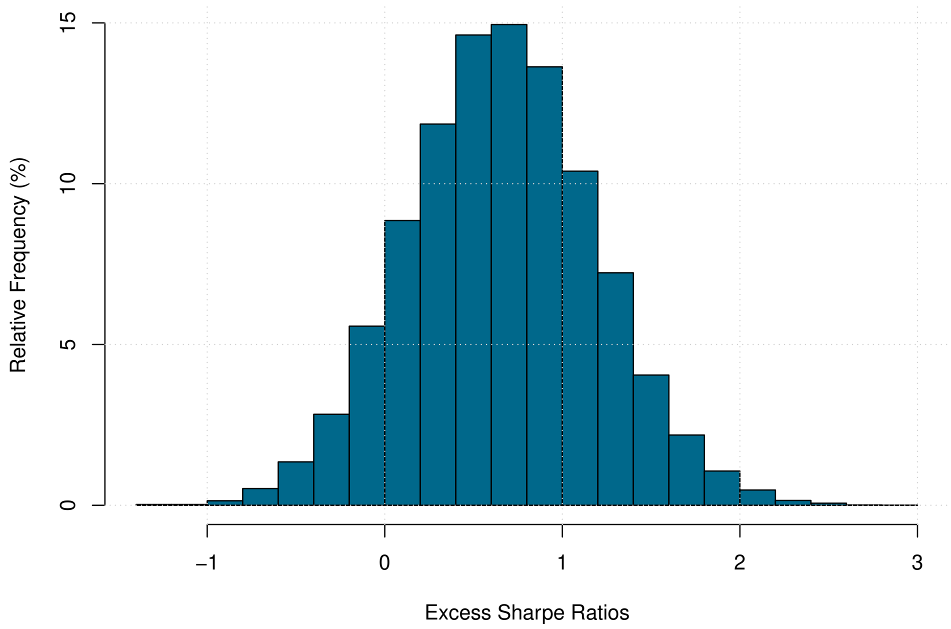


Figure B.13: This chart shows the excess return for our empirical backtests based on the MSCI World Index.
Note: We test the commodity channel index on its robustness by applying it on 20,000 simulated price paths. We use a lookback period of 20 days and use 100 as the upper and -100 as the lower signal threshold, respectively. The Sharpe ratio, as defined in Equation 2.20, is $\widehat{\text{SR}}_k = \frac{\hat{\mu}_k}{\hat{\sigma}_k}$. We subtract $\widehat{SR}_{BH}$ from $\widehat{SR}_k$ to get the amount by which the active strategy, k, delivers an improved Sharpe ratio relative to the passive strategy, *BH*.

Skewness	CCI	BH
Min. :	-3.86732	-13.60131
1st Qu.:	0.36287	-0.87940
Median :	0.83429	-0.61466
Mean :	1.05353	-0.73680
3rd Qu.:	1.44245	-0.43446
Max. :	22.61658	1.16424
S(CCI) > S(BH):	96.17%	

Figure B.14: This figure shows the skewness information for the asset MSCI World Index.
Note: The tested indicator is the commodity channel index, CCI; the tested time period ranges from January 2005 to September 2016. Column *BH* reports the results for the buy-and-hold strategy.

Kurtosis	CCI	BH
Min. :	6.4247	1.3505
1st Qu.:	14.8455	4.4888
Median :	19.3865	6.2001
Mean :	25.8432	8.6394
3rd Qu.:	27.5601	9.2430
Max. :	895.3197	388.7687
K(CCI) > K(BH):	99.575%	

Figure B.15: This figure shows the kurtosis information for the asset MSCI World Index.
Note: The tested indicator is the commodity channel index, CCI; the tested time period ranges from January 2005 to September 2016. Column *BH* reports the results for the buy-and-hold strategy.

3 Factor-Based Tactical Bond Allocation and Interest Rate Risk Management[1]

3.1 Introduction

This paper tackles two major issues faced by asset allocation committees when determining how to position in the sovereign bond market. By creating trading signals based on a factor strategy, we are firstly told whether we should be invested in bonds at all rather than holding cash and vice versa, and secondly—if we are invested in bonds—whether we should be positioned in short- or long-duration bonds. To obtain trading signals for each market, we select four factors, which are combined to form a composite bond market factor strategy. The factors used in this paper are based on existing financial research, and, as such, are no novelty. However, we show that a selection of economically meaningful factors, which are already present in the financial literature, help us improve our investment performance—relative to being passively invested as a buy-and-hold investor—by following a systematic, yet simple approach. An additional benefit of having a factor model to indicate an optimal positioning is the reduction of the poor decision-making caused by human biases. As bond market investors are primarily interested in whether yields are going to rise or fall in the near future, we aim to develop a model that predicts the future development of excess bond returns over cash. Since the aftermath of the financial crisis, interest rates have experienced new lows, sometimes even negative values, and fears of an inverse term structure have arisen. The "new bond market environment", with record low yields and strong interventions by central banks, and well-performing and highly supported stock markets backed by convincingly strong economic fundamentals makes it more difficult and riskier to invest in bonds, as central banks have to normalize their monetary policies at some point, which would imply higher yields and therefore falling bond prices. It is therefore our objective to develop a bond market factor strategy that would, historically, have performed well when interest rates were raised. We conduct our empirical analysis on data from various countries; in the main paper we report the results for Switzerland and the world as a whole, whereas additional results for the USA, Germany, Japan, the UK, Australia, and Canada can be found in our online appendix[2], available on request. Our paper is split into a theoretical part and an empirical part. The former starts with Section 3.2, where we explain our four factors and how we construct the bond market factor and is followed by Section 3.3, in which we show how the performance metrics used in the empirical part are calculated. Section 3.4 contains a description of the dataset used in our empirical analysis along with additional information on how we chose which data series to use for the Swiss and global cases. For the empirical part of this paper, we report

[1]This paper should be cited as Thomann, A. (2018), "Factor-Based Tactical Bond Allocation and Interest Rate Risk Management". A modified version of this paper has been submitted to the *Journal of Investment Strategies*.
[2]Link to the online appendix.

the backtesting results in Section 3.5; however, we also formally describe how the investment strategies are set up. After providing the empirical results of our market timing and duration switching investment strategies, we discuss their drawdown behavior in Section 3.6, where we put the focus on improvements on drawdowns experienced relative to the buy-and-hold strategy in periods of rising interest rates to proxy the bond market factors' behavior during the coming tightening of monetary policy. We conclude our paper with a short summary of our main results in Section 3.8.

3.2 Bond Market Factor

In this section of the paper we introduce the underlying model of our bond market factor. First, we start with four findings that we are trying to exploit in our bond market factor strategy. Applied financial research in particular (see for example J.P. Morgan's study by Kolanovic et al. (2018) or Morgan Stanley's study by Hornbach et al. (2015)) states, that excess bond returns are high if:

1.) carry is high and the yield curve steep

2.) previous bond returns have been positive

3.) previous equity returns have been low or negative

4.) the business cycle is slowing and/or surprises have been negative

Based on the above observations, we develop the individual factors and describe how they are constructed, how we adjust the signals, and how the individual factors are used to build a composite bond market factor. To do so, we follow the approach of Hornbach et al. (2015). As the goal of the model is to determine the trade-off between cash and bonds and between short- and long-duration bonds, the factors used to build our bond market factor strategy are based on variables that have been proven to have predictive value in generating excess bond returns over cash in the existing literature. To exploit the aforementioned regularities of excess bond returns we construct carry, bond market momentum, equity market performance, and business cycle factors. While the first two factors, carry and bond market momentum, have their foundation in the bond markets themselves, the last two have their rationale in the risk-off behavior, when investors typically shift from risky assets such as equities into less risky assets such as sovereign bonds once economic conditions deteriorate. While these four factors are economically reasonable, as a group they combine macroeconomic and style factors. We use both types of factor as each has distinct characteristics in different market environments; we therefore expect to improve the combined signal by using a combination of both.

3.2.1 Carry

Our carry strategy's goal is to harvest the term premium resulting from a steep yield curve. For this to be profitable, the realized yield has to be lower than the initial forward yield—which, in turn, implies rising bond prices (see for example Korapaty and Thakkar (2018)). The expectations hypothesis—a fundamental theorem in fixed income markets—is used to forecast future short-term interest rates based on current long-term interest rates. This theorem implies that carry strategies should not be successful, as the forward yields are taken to be the market's expectation of future yields. However, Fama (1976), among others, shows that forward yields predict future spot rates badly, and that more positive carry is an unlikely reason for rates to rise. A steeper yield curve implies higher carry and therefore higher excess bond returns (see for example Mueller-Glissmann et al. (2018)). The signal indicating a favorable environment is calculated as a full-sample z-score (expanding from the start date) of the 10–2-year treasury yield curve adjusted for volatility by dividing it by the 1-year realized volatility. Using a rescaled logistic sigmoid function[3], we normalize the signal to cap its strength when it reaches extreme values. The value of the signal is bound to be in the range of ± 10. This normalization prevents the signal from reaching too extreme values.

3.2.2 Bond Market Momentum

Trend-following and momentum strategies are documented in various studies for different asset classes (see, among others, Jegadeesh and Titman (1993)), and we also include the momentum factor as as one of the individual factors to be incorporated into our composite bond market factor. We calculate our bond market momentum factor as the difference between the excess return at $t-1$ and an exponential moving average with a lookback period of four months. This differential is divided by volatility with the same lookback period. To prevent us from removing long-term trends in the data, we normalize the signal to the ± 10 span directly.

3.2.3 Equity Market Performance

As, among others, Ilmanen (1995) documents, risk aversion is strongly dependent on the investor's wealth. Therefore, as risk aversion can change with changing wealth, so can the observed risk premiums. With declining wealth, investors demand a higher premium for holding risky assets. In order to protect their wealth against potential losses, investors simultaneously demand a lower rate of return from a safer asset. Investors are therefore willing to shift into less risky sovereign bonds if risk aversion rises due to a correction or crash in the stock market. We construct a full sample z-score signal that is based on local equity returns with a lookback period of 3-months. We extend this signal with the z-score of the equity market performance difference between emerging and developed markets. We use this extension as a complement, because if risky assets perform strongly, emerging market equities tend to outperform developed market equities and vice versa. The final signal is a simple average of both signals, again fitted into the ± 10 span using the logistic sigmoid function described in Subsection 3.2.1.

3.2.4 Business Cycle

Fama and French (1989) find that the variation of the term spread is linked to changes in the business cycle. Typically, the business cycle troughs and the steepest point of the yield curve are observed simultaneously. This also implies high bond returns as business conditions worsen,

[3] We use the hyperbolic tangent function (tanh function) to rescale the output to ± 10. The logistic sigmoid function is $g(x) = \frac{\exp^x}{1+\exp x}$, where tanh is defined as: $tanh(x) = 2g(2x) - 1$.

while bonds normally suffers in strong a macroeconomic environment (see for example Normand (2017)). This rationale is in line with the argumentation of Subsections 3.2.1 and 3.2.3 as equities typically perform strongly in healthy macroeconomic environments. The business cycle factor is therefore a contra-indicator, meaning that if business conditions surprise positively, we reduce our bond exposure, and increase it if conditions worsen. As in Subsection 3.2.2, we allow for trends in the data.

3.2.5 Composite Factors: Collection and Overall

Albeit we have four signals resulting from our individual factor strategies described above, we prefer to have one composite signal that indicates how to position in the bond markets. To do so, we calculate the *Collection* factor, *COL*, which is the simple average of the four individual factors: carry, bond market momentum, equity market performance, and business cycle. In contrast to the *Collection* signal, the *Overall* signal, OVL, is truncated around a centered value, where the signal is considered as weak and unconvincing. In our base case, the *Overall* signal is set to zero if the *Collection* signal shows only little conviction, which we define as a signal strength of ± 1.5. Therefore, the *Overall* factor is more restrictive in terms of signal validity, gives fewer signals, and therefore allows less aggressive positioning than the *Collection* factor does. We interchangeably use the factor names *Collection* and *Overall*, their abbreviations *COL* and OVL, and the more descriptive names untruncated and truncated bond market factor strategy, respectively.

3.3 Performance Evaluation

To compare the empirical results of our backtests we evaluate the performance of our investment strategies using different metrics. While the focus of our analysis is on the standard industry performance metrics including Sharpe ratio, annualized return, and volatility, as well as maximum drawdown, we also report a variety of additional ratios, which extend the information gained from using the Sharpe ratio and therefore extend our analysis.

3.3.1 Sharpe Ratio

The Sharpe ratio is defined as the strategy's mean of excess returns over the risk-free asset, $\overline{(R_P - R_{rf})}$, divided by its standard deviation, $\sqrt{\operatorname{var}(R_P - R_{rf})}$. We set the risk-free return equal to zero. Formally, the Sharpe ratio of our strategy is defined as

$$\text{Sharpe ratio} = \frac{\overline{(R_P - R_{rf})}}{\sqrt{\operatorname{var}(R_P - R_{rf})}}. \tag{3.1}$$

3.3.2 Maximum Drawdown

Maximum drawdown is defined as the largest drop from peak to trough over a certain period of time, $[0, T]$. Mathematically speaking, if $v_t(x)$ is the net asset value of a trading strategy at time t, the drawdown function at time t is defined as the difference between the maximum of this function and the value of this function at time t. From the drawdown function, the

maximum drawdown can be determined by choosing its maximum value over the entire time interval, $[0, T]$.
Formally, the maximum drawdown of strategy k is defined as

$$\mathrm{MDD}_k = \max_{0 \leq t \leq T} \left(\frac{\max_{0 \leq \tau \leq t}[v_\tau(x)] - v_t(x)}{\max_{0 \leq \tau \leq t}[v_\tau(x)]} \right) \cdot (-1)\,. \tag{3.2}$$

3.3.3 Sortino Ratio

In contrast to the Sharpe ratio, which is based on volatility, the ratio defined in Sortino and Price (1994) is focused on downside risk. Downside risk, or more specifically downside deviation in our case, ignores positive returns and instead uses the minimum acceptable return, MAR, to capture the performance lower than this minimum threshold. To calculate the downside risk, we calculate the square of the difference of all returns smaller than the MAR to the MAR itself and divide this value by the number of returns, n. We set MAR = 0%.

$$\text{Sortino ratio} = \frac{\overline{R_P - \mathrm{MAR}}}{\sqrt{\sum_{t=1}^{n} \frac{\min[(R_{P,t} - \mathrm{MAR}), 0]^2}{n}}}. \tag{3.3}$$

3.3.4 Bernardo and Ledoit Ratio

The Bernardo and Ledoit ratio—also referred to as the Omega ratio—is defined as the sum of positive returns divided by the sum of negative returns (see Bernardo and Ledoit (2000)).

$$\text{Bernardo and Ledoit ratio} = \frac{\frac{1}{n}\sum_{t=1}^{n} \max(R_t, 0)}{\frac{1}{n}\sum_{t=1}^{n} \max(-R_t, 0)}. \tag{3.4}$$

3.3.5 Modified Burke Ratio

To calculate the Burke ratio we subtract the risk-free rate from the portfolio return, $(R_P - R_{rf})$, and divide it by the square root of the sum of the square of the drawdowns. We report the modified Burke ratio, which is the Burke ratio multiplied by the square root of the number of observations. We set the risk-free return equal to zero.

$$\text{Modified Burke ratio} = \frac{(R_P - R_{rf})}{\sqrt{\sum_{t=1}^{d} \frac{D_t^2}{n}}}. \tag{3.5}$$

3.3.6 Calmar Ratio

To calculate the Calmar ratio, we divide the annualized return by the absolute value of the maximum drawdown the strategy experienced.

$$\text{Calmar ratio} = \frac{R_{ann}}{|MDD|}. \tag{3.6}$$

3.4 Data

The data we use in our empirical analysis can be split into two subsets. The first contains the bond return series, for which we decide to use the country-specific Citigroup GBI bond series and use the Bloomberg Terminal to collect the data. For Switzerland, we store daily return observations for the 3–5- and 7–10-year duration bonds, while for the global bond market we collect the 7–10 year Citigroup WGBI data. We store principal and total return data for all these time series. While we calculate the bond market factors for Switzerland and the world as a whole ourselves, the factors for the other countries are calculated by Morgan Stanley. Below, in Table 3.2, we provide an overview of all the series used in the empirical analysis[4].

Table 3.1: This table lists the principal and total return series used for our empirical analysis. The data was collected using the Bloomberg Professional Terminal and is calculated by Citigroup. For Switzerland we collect short- (3–5 year) and long-term (7–10 year) bond series, whereas globally we only collect the long-term (7–10 year) bond series. Every bond series is in local currency.

Series Name	Region	Currency	First Date
Citigroup GBI Switzerland 3–5 Year	Switzerland	CHF	1999-04-30
Citigroup GBI Switzerland 7–10 Year	Switzerland	CHF	1999-04-30
Citigroup WGBI 7–10 Year	World	USD	1994-06-02

3.4.1 Switzerland

As a major contribution of this paper we develop and construct the four individual and two composite bond market factors for Switzerland, as we are particularly interested in having a model that also covers Switzerland as it is a major region in the investment industry and widely considered a safe haven in times of stressed financial markets. While the bond market momentum factor is based on the bond return series itself, we have to collect additional data for the carry factor, equity market performance, and business cycle factor (all listed in Table 3.2). To calculate our carry factor, we use the ten- and two-year Swiss government yield data, provided by Bloomberg. To construct the business cycle factor, we use the KOF Economic Barometer, which is published by the KOF Swiss Economic Institute. It is a leading composite indicator, predicting how the Swiss economy is expected to perform in the near future. For the equity market performance factor, we use, first, the Swiss Performance Index (SPI) total return series. It contains almost all the stocks of companies that are domiciled in either Switzerland or Liechtenstein. To calculate the second equity market signal, the emerging markets versus developed markets performance differential, we use the daily return data of the MSCI USA, MSCI Europe Ex Switzerland, and MSCI Emerging Markets indices. The factor construction itself follows the methodology as outlined in Subsections 3.2.1 to 3.2.4. For the drawdown analysis in Section 3.6, we collect daily observations of the 3-month LIBOR data provided by the Swiss National Bank

[4] In the data section we list all data used for the empirical tests in the main paper. The data used for robustness checks and other countries are reported in the online appendix, which can be found here.

for the same period as that for which we have factor data.

3.4.2 World

To construct the four individual bond market factors for the global bond market, we calculate the equally weighted average across all the available regional factors. The four individual global factors are then manipulated as described above in Subsection 3.2.5 to model the global composite bond market factors COL and OVL.

Table 3.2: This table lists all the input factors used to calculate the bond market factors for our empirical analysis in pane a. The data was collected using the Bloomberg Professional Terminal and was calculated by the author. Pane b of this table, we report the data used for drawdown analysis in Section 3.6. It was downloaded from the Swiss National Bank's data repository.

Factor/*Input Data Series*	**Region**	**First Date**
Pane a		
Bond Market Factor Switzerland Business Cycle	Switzerland	1999-04-30
KOF Economic Barometer		
Bond Market Factor Switzerland Carry	Switzerland	1999-04-30
Government Bond 10-Year Yields		
Government Bond 2-Year Yields		
Bond Market Factor Switzerland Equities	Switzerland	1999-04-30
Swiss Performance Index		
MSCI USA Index	*USA*	
MSCI Europe Ex Switzerland Index	*Europe*	
MSCI Emerging Markets Index	*Emerging Markets*	
Bond Market Factor Switzerland Momentum	Switzerland	1999-04-30
Citigroup GBI 3–5 Year		
Citigroup GBI 7–10 Year		
Bond Market Factor Switzerland Overall	Switzerland	1999-04-30
Bond Market Factor World Business Cycle	World	1994-06-02
Bond Market Factor Australia Business Cycle	*Asia*	
Bond Market Factor Canada Business Cycle	*North America*	
Bond Market Factor Germany Business Cycle	*Europe*	
Bond Market Factor Japan Business Cycle	*Asia*	
Bond Market Factor UK Business Cycle	*Europe*	
Bond Market Factor US Business Cycle	*USA*	
Bond Market Factor World Carry	World	1994-06-02
Bond Market Factor Australia Carry	*Asia*	
Bond Market Factor Canada Carry	*North America*	
Bond Market Factor Germany Carry	*Europe*	
Bond Market Factor Japan Carry	*Asia*	
Bond Market Factor UK Carry	*Europe*	
Bond Market Factor US Carry	*USA*	
Bond Market Factor World Equities	World	1994-06-02
Bond Market Factor Australia Equities	*Asia*	
Bond Market Factor Canada Equities	*North America*	
Bond Market Factor Germany Equities	*Europe*	
Bond Market Factor Japan Equities	*Asia*	
Bond Market Factor UK Equities	*Europe*	
Bond Market Factor US Equities	*USA*	
Bond Market Factor World Momentum	World	1994-06-02
Bond Market Factor Australia Momentum	*Asia*	
Bond Market Factor Canada Momentum	*North America*	
Bond Market Factor Germany Momentum	*Europe*	
Bond Market Factor Japan Momentum	*Asia*	
Bond Market Factor UK Momentum	*Europe*	
Bond Market Factor US Momentum	*USA*	
Bond Market Factor World Overall	World	1994-06-02
Bond Market Factor Australia Overall	*Asia*	
Bond Market Factor Canada Overall	*North America*	
Bond Market Factor Germany Overall	*Europe*	
Bond Market Factor Japan Overall	*Asia*	
Bond Market Factor UK Overall	*Europe*	
Bond Market Factor US Overall	*USA*	
Pane b		
Swiss National Bank 3-month LIBOR	Switzerland	1999-04-30

3.5 Factor Investment Strategies

In this section, we explain how the factors described in Section 3.2 are translated into a tradeable bond market investment strategy that supports our efforts to obtain a view on bond market duration and guides us in our tactical interest rate market view. We divide our empirical analysis into two parts: The first is referred to as the "market timing strategy", as we are either invested in bonds or move to cash (or vice versa). We call the second strategy the "duration switching strategy" as the model tells us whether we should be invested in short- or long-term bonds.

3.5.1 Market Timing Strategy

The market timing strategy is either invested in bonds or holds cash. While our benchmark strategy always holds cash, we also report the performance of the buy-and-hold strategy's investment in bonds of the same duration as the investments of the market timing strategy. We do this as some of the performance metrics can not reasonably be benchmarked to cash, as it does not generate returns and does not experience volatility and drawdowns[5]. Mathematically, we can formulate the active trading decision as follows:

$$\text{Market timing} = \begin{cases} \text{invested in bonds if:} & \text{factor} > \text{x} \\ \text{holds cash if:} & \text{factor} \leq \text{x} \end{cases}. \tag{3.7}$$

The strategy in this section is tested in a long-only environment.

Region: Switzerland
7–10 Years

Table 3.3: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part this paper. The table reports the tests for the region Switzerland. The tested time period spans from 1999-04-30 until 2017-03-30. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	CYC	CRY	EQY	MOM	COL	OVL
Ann. Return	0.0241	0.0179	0.0147	0.0175	0.0207	0.0208	0.0215
Ann. Std Dev	0.0297	0.0215	0.0191	0.0224	0.0222	0.0215	0.0216
Ann. Sharpe	0.8107	0.8320	0.7657	0.7844	0.9293	0.9677	0.9932
Max. Drawdown	0.0924	0.0458	0.0462	0.0600	0.0484	0.0426	0.0426
Avg. Drawdown	0.0076	0.0065	0.0059	0.0072	0.0064	0.0058	0.0059
Avg. Length	36.8671	49.8482	53.9091	57.6569	51.4590	47.3939	46.6269
Avg. Recovery	17.1456	29.9643	27.1364	38.3235	32.5246	31.9697	31.5299
Sortino	0.0754	0.0800	0.0723	0.0746	0.0897	0.0936	0.0961
Bernardo & Ledoit	1.1879	1.3124	1.2608	1.2784	1.3018	1.3486	1.3533
Mod. Burke	13.6487	14.3884	13.3720	13.5046	16.5102	16.9097	17.3909
Calmar	0.2606	0.3909	0.3170	0.2925	0.4270	0.4875	0.5035

[5] Assuming cash to be a zero-return investment.

As the market timing strategy is either holding cash or is invested in bonds and the reported benchmark is always invested in bonds, we expect our factor strategies to have higher Sharpe ratios as a result of lower volatility overcompensating lower return figures. Our bond market factors, both truncated and untruncated, generate a higher Sharpe ratio, as expected due to lower volatility despite generating lower returns. Truncating the signal around ±1.5 also improves the annualized return; however, it remains lower than the return delivered by following a passive buy-and-hold strategy. The *Collection* as well as the *Overall* strategy reduce the maximum drawdown by more than 50%. Exiting the bond market, however, also a implies longer average drawdowns and longer recovery periods. Every individual factor experiences a lower volatility than the benchmark strategy does, with reduced annual return too. Maximum drawdown is also significantly reduced by each individual factor. As for the *Overall* bond market factor strategy, every individual signal reduces the maximum drawdown approximately by half but again at the expense of a higher average drawdown length and longer recovery period. These observations translate into higher Bernardo and Ledoit and Calmar ratios. While the modified Burke ratio is slightly lower than the one reported for the buy-and-hold strategy, every other factor achieves a higher ratio. From an individual factor perspective, bond market momentum is performing best, with the overall highest Sharpe ratio as a result of having the highest individual annualized return, while experiencing the second highest volatility. These strong factor properties are also reflected in the other performance metrics, such as the Calmar, Sortino, and modified Burke ratios.

3–5 Years

Table 3.4: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Switzerland. The tested time period spans from 1999-04-30 until 2017-03-30. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0162	0.0125	0.0099	0.0113	0.0123	0.0132	0.0134
Ann. Std Dev	0.0149	0.0115	0.0100	0.0117	0.0118	0.0115	0.0115
Ann. Sharpe	1.0837	1.0893	0.9907	0.9585	1.0444	1.1476	1.1615
Max. Drawdown	0.0441	0.0367	0.0198	0.0308	0.0363	0.0255	0.0255
Avg. Drawdown	0.0037	0.0033	0.0030	0.0035	0.0033	0.0028	0.0029
Avg. Length	35.7471	48.1121	50.1488	61.4896	51.7899	46.4697	47.1692
Avg. Recovery	17.7471	23.4310	26.5372	39.5729	22.0840	28.1364	28.6923
Sortino	0.1023	0.1070	0.0968	0.0919	0.1020	0.1131	0.1144
Bernardo & Ledoit	1.2653	1.4484	1.3461	1.3744	1.3513	1.4363	1.4347
Mod. Burke	19.2436	19.9620	18.3188	17.3854	19.3057	21.1295	21.4040
Calmar	0.3670	0.3405	0.4992	0.3653	0.3382	0.5161	0.5261

In the short-term case, both composite strategies outperform the benchmark strategy in terms of Sharpe ratio as the lower volatility can compensate for the reduced annualized return. Additionally, experienced worst and average drawdowns are lower than those of the benchmark strategy. As the Sortino, Bernardo and Ledoit, and the modified Burke ratios are all better than those of the benchmark strategy, the results for our composite strategies are highly promising. Truncating the signal at ±1.5 yields an improvement of Sharpe ratio by raising the annualized return while keeping the volatility constant. The *Overall* strategy is still able to keep the worst and average drawdowns below those experienced by the passive strategy. As for the untruncated version of the bond market factor, the Sortino, Bernardo and Ledoit, and modified Burke ratios are all better than for the benchmark case. As for the long-term bonds, the bond market momentum factor still performs strongly, while the cycle factor stands out as the outperforming contributor, yielding the highest annualized return and thereby generating the highest individual Sharpe ratio. The equities factor attracts our attention as the worst performer, with too low annualized-return and too high volatility figures to beat the benchmark strategy on the Sharpe ratio level. However, every individual factor reduces the worst and average drawdowns relative to the benchmark strategy.

Region: World
7–10 Years

Table 3.5: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region World. The tested time period spans from 1994-06-02 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	CYC	CRY	EQY	MOM	COL	OVL
Ann. Return	0.0297	0.0224	0.0257	0.0149	0.0380	0.0208	0.0359
Ann. Std Dev	0.0650	0.0459	0.0519	0.0448	0.0523	0.0521	0.0535
Ann. Sharpe	0.4573	0.4870	0.4952	0.3329	0.7269	0.3989	0.6713
Max. Drawdown	0.1227	0.1336	0.1252	0.1047	0.1056	0.1236	0.1121
Avg. Drawdown	0.0201	0.0189	0.0179	0.0173	0.0139	0.0179	0.0157
Avg. Length	62.7195	95.2364	80.7841	118.0351	54.9603	81.2188	56.6835
Avg. Recovery	32.3171	64.6364	39.1818	73.4035	30.7483	34.0000	28.4820
Sortino	0.0443	0.0468	0.0475	0.0324	0.0714	0.0387	0.0653
Bernardo & Ledoit	1.1028	1.1582	1.1449	1.1100	1.2009	1.1149	1.1877
Mod. Burke	8.1390	8.9110	8.9063	6.1147	13.9224	7.2680	12.7257
Calmar	0.2422	0.1674	0.2051	0.1424	0.3602	0.1682	0.3204

While the simple world bond market strategy without truncation fails to outperform the buy-and-hold strategy in most reported performance metrics, truncating unconvincing signals at ±1.5 improves the *Overall* composite factor, beating the buy-and-hold strategy on every reported metric apart from the average drawdown length. Truncation additionally reduces the average and worst drawdowns. For the first time, the average recovery period is smaller when applying our *Overall* composite factor than when following the buy-and-hold approach. From an individual factor perspective, bond market momentum is by far the best performing component. Generating by far the highest annualized return with a reasonable volatility, we report the highest Sharpe ratio for bond market momentum across the factors. While it performs comparably with the other factors when looking at the maximum drawdown, it performs best in terms of average drawdown. Across the ratios reported at the bottom of Table 3.5, bond market momentum achieves the best results. Equity, on the other hand, is the worst performing individual factor. Even though the equity strategy experiences the lowest volatility, this comes at the expense of the lowest annualized return. This fact weighs heavily and also diminishes the strategy's Sharpe ratio. This result is in line with the other performance metrics, for which the equity market performance factor shows the worst results.

3.5.2 Duration Switching Strategy

The duration switching strategy is invested in either short- or long-term bonds. If the bond market factor indicates a good environment for bond investments, we are invested in long-term bonds, whereas we invest in short-duration bonds if the factor signals worsening circumstances, to reduce bond market risk. In terms of risk taking, the duration switching strategy is a more aggressive model than the market timing strategy from Subsection 3.5.1, as it never leaves the bond market entirely and remains invested, thereby remaining exposed to interest rate risk. Mathematically, we can formulate the active trading decision as follows:

$$\text{Duration switching} = \begin{cases} \text{invested in long-term bonds if:} & \text{factor} > \text{x} \\ \text{invested in short-term bonds if:} & \text{factor} \leq \text{x} \end{cases}. \tag{3.8}$$

The strategy in this section is tested in a long-only environment. The benchmark strategy is always invested in long-term bonds. Again, the official benchmark is cash but we report the performance achieved by a buy-and-hold investment strategy (cp. with the reasoning in Subsection 3.5.1).

Region: Switzerland

Table 3.6: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Switzerland. The tested time period spans from 1999-04-30 until 2017-03-30. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	CYC	CRY	EQY	MOM	COL	OVL
Ann. Return	0.0241	0.0216	0.0210	0.0225	0.0246	0.0237	0.0244
Ann. Std Dev	0.0297	0.0235	0.0221	0.0242	0.0241	0.0234	0.0235
Ann. Sharpe	0.8107	0.9174	0.9486	0.9289	1.0221	1.0110	1.0347
Max. Drawdown	0.0924	0.0458	0.0774	0.0659	0.0550	0.0550	0.0550
Avg. Drawdown	0.0076	0.0061	0.0060	0.0057	0.0064	0.0060	0.0061
Avg. Length	36.8671	41.0000	39.2452	35.9706	40.8750	38.9497	39.4713
Avg. Recovery	17.1456	24.2434	23.0774	19.2941	22.9803	22.0189	22.0955
Sortino	0.0754	0.0871	0.0888	0.0877	0.0974	0.0964	0.0987
Bernardo & Ledoit	1.1879	1.2389	1.2366	1.2392	1.2599	1.2662	1.2703
Modified Burke	13.6487	15.8197	16.4851	15.9822	17.9782	17.5593	17.9998
Calmar	0.2606	0.4712	0.2713	0.3406	0.4469	0.4303	0.4427

As we no longer move into cash once the factor signal shows us a worsening of the bond market environment, but rather move from long duration into short duration, we do not leave as much return potential on the table. This fact is clearly visible in terms of annualized returns, compared to the reported return data in Tables 3.3 and 3.4. On the other hand, we are still exposed to interest rate change risk. However, as the backtesting results for the untruncated, *Collection* factor strategy show, this pays off: Even though the annualized return is lower than for the passive strategy, the lower volatility of our *Collection* strategy overcompensates for this, which is reflected in a higher Sharpe ratio. Both average and worst drawdowns are improved by applying the active strategy, while the latter is reduced by almost 50%. Satisfyingly, the other performance ratios also favor our *Collection* strategy. Apart from volatility and drawdown-related figures, removing unconvincing signals at ±1.5 significantly improves every single reported metric. Therefore, in summary, for the duration switching model truncation pays off. Again, on average, bond market momentum turns out to be the best performing individual factor. Apart from equities, every other active factor (individually or combined) has worse properties in terms of average drawdown period and recovery period, but outperforms the benchmark strategy in every other reported metric apart from annual return. While the other individual factors are also unable to beat the benchmark in terms of average recovery period, the equity factor successfully reduces average drawdown length but insignificantly. Cycle, as a standalone component, performs surprisingly strongly in drawdown management, experiencing the lowest maximum drawdown. In summary, the duration switcher for Switzerland performs strongly across all individual components, therefore supporting the decision to use all four factors as inputs to the *Overall* strategy. As mentioned above, signal truncation is beneficial across every reported metric, supporting the case for removing unconvincing signals. However, we have to bear in mind that we have experienced years of declining interest rates, with only few interest rate hikes.

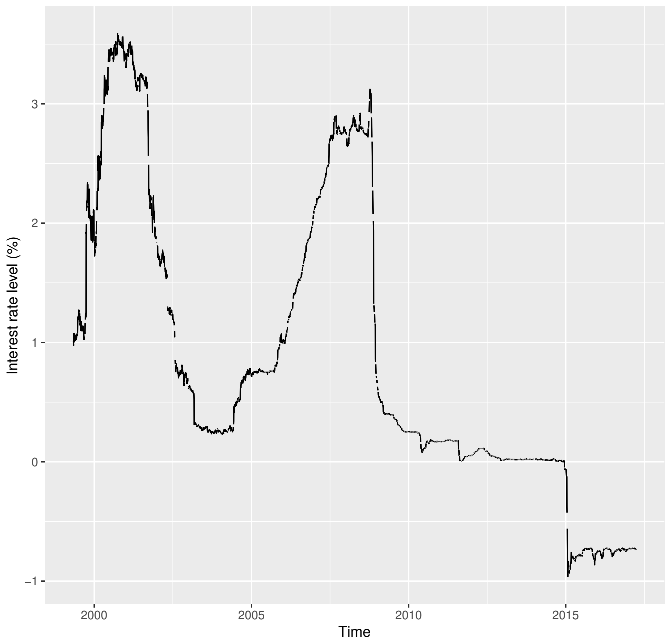
3.6 Drawdown Behavior

Changes in interest rates are the most important risk factor to consider when investing in sovereign bonds. We therefore analyze the largest drawdowns found in the Swiss long-term returns series. The inverse relationship of interest rates and bond prices implies that rising interest rates are reflected in lower bond prices, which again should be mirrored in our return data [6]. Looking at the development of interest rates in Switzerland, we should therefore be able to detect the same periods as observed using the drawdown analysis of our in principal return data.

From Figure 3.1 we can summarize that there were three major periods of rising interest rates during our empirical backtesting window. Right at the beginning of the chart, in Spring 1999, was the starting point of the first interest rate increase, the rate rising to 3.57% by October 2000. The second example of a rising interest rate environment began in January 2004, the rate rising from 0.24% to reach 3.13% in October 2008. From June 2010 to May 2011 we detect another period of rising interest rates—although this time significantly lower in magnitude. We can thus build three major consecutive periods of rising interest rates:

[6] This rationale is reaffirmed when we look at the interest data provided by central banks, taking the Swiss case as representative example.

Figure 3.1: Swiss National Bank 3-month LIBOR: This plot shows the Swiss 3-month LIBOR rate as an indicator for interest rate levels in Switzerland. The data plotted in this chart spans from 1999-04-29 until 2017-03-30.



1) 1999-04–2000-10

2) 2004-01–2008-10

3) 2010-06–2011-05

In order to assess the quality of our factor strategies, we first extract the largest drawdowns found in our principal return series as a proxy for interest rate increases and then extract the largest drawdowns experienced when following our active, factor-based investment strategy. While we use the principal return data to reaffirm that changes in interest levels are reflected in our price series, we use total return data to compare the performance of our factor investment strategies relative to the buy-and-hold strategy.

Principal Return

Table 3.7, below, reports the drawdowns detected in the long-duration principal return bond data for Switzerland. Strikingly, we observe that 6 out of 10 of the largest drawdowns in Table 3.7 were larger than 50%, with the largest occurring from May 1999 to January 2003 with a depth of 98.25%. Obviously, these are not drawdowns we would expect from a reasonable passive sovereign bond investment—but we have to keep in mind that these figures are principal return data and not total return data, which we will discuss later. In the list that follows, we present the periods in which the highest drawdowns in principal returns are detected:

1) 1999-05–2003-01

2) 2005-06–2010-05

3) 2010-09–2011-09

Comparing these periods with our findings based on the interest rate data provided by the Swiss National Bank, we find that the periods of rising interest rates and the largest drawdowns in principal return data do indeed overlap, and therefore affirm the inverse relationship of interest rates and bond prices. Therefore, cross-comparing the periods in which the highest drawdowns in the principal return data are observed with the Swiss National Bank's interest rate policy (see Figure 3.1), we recognize that the three worst drawdowns occurred during the three major restrictive monetary policy periods when interest rates increased significantly. While the drawdown periods are longer than the periods of rising interest rates, the peaks in interest rate levels and the drawdown troughs are observed around the same dates. This supports our thesis and we therefore move to the total return analysis.

Table 3.7: This table shows the largest drawdowns detected in the long-term principal return data for the region Switzerland. The tested time period spans from 1999-04-29 until 2017-03-30.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1999-05-31	2000-06-29	2003-01-11	-0.9825	1322	396	926
2	2005-06-30	2008-07-30	2010-05-17	-0.9701	1783	1127	656
3	2010-09-30	2011-05-30	2011-09-21	-0.8317	357	243	114
4	2012-08-31	2014-01-30	2015-02-22	-0.8268	906	518	388
5	2003-03-31	2004-07-30	2005-05-07	-0.7999	769	488	281
6	2015-12-31	2016-01-30	2016-04-17	-0.5343	109	31	78
7	2015-02-28	2015-07-30	2015-12-19	-0.4106	295	153	142
8	2012-06-30	2012-07-30	2012-08-28	-0.3016	60	31	29
9	2012-02-29	2012-04-29	2012-06-08	-0.2814	101	61	40
10	2011-10-31	2011-11-29	2011-12-28	-0.1657	59	30	29

Buy-And-Hold

First and foremost we observe in Table 3.8 that the drawdown depth is both significantly lower compared to the results reported in the previous part based on principal return data (see Table 3.7) and in an expected range for bond investments.

Table 3.8: This table shows the largest drawdowns detected in the long-term total return data for the region Switzerland. The tested time period spans from 1999-04-29 until 2017-03-30.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1999-04-30	2000-05-19	2001-03-22	-0.0924	693	386	307
2	2005-09-23	2007-07-09	2008-01-23	-0.0662	853	655	198
3	2010-08-25	2011-04-11	2011-07-27	-0.0543	337	230	107
4	2003-06-12	2003-09-03	2004-03-08	-0.0515	271	84	187
5	2001-11-08	2002-03-08	2002-06-26	-0.0458	231	121	110
6	2012-12-11	2013-09-10	2014-05-08	-0.0453	514	274	240
7	2008-03-25	2008-06-19	2008-08-13	-0.0441	142	87	55
8	2003-03-12	2003-04-07	2003-06-10	-0.0410	91	27	64
9	2004-03-16	2004-06-29	2004-10-11	-0.0376	210	106	104
10	2015-01-26	2015-06-10	2015-11-10	-0.0342	289	136	153

For the total return long-term bond data we observe three major drawdown periods, namely:

1) 1999-04–2001-03

2) 2005-09–2008-01

3) 2010-08–2011-07

The periods overlap with the major increases in interest rates as depicted in Figure 3.1. The worst drawdown detected in the long-term total return series is 9.24%, followed by one of 6.62% and three smaller drawdowns of around 5%. Again, the drawdown periods are longer than the periods of rising interest rates, as the bonds need time to recover the losses. Setting this information to one side to be referred back to during the relative evaluation of the performance of our factor strategies allows us to move on to an analysis of drawdowns experienced when using the bond market factors.

Factor: Overall

As the *Overall* strategy is our final product and should be used as the guiding tool in the asset allocation process, we start our drawdown analysis with it[7]. Our first observation clearly is that even the largest drawdown, which occurred between March 2003 and December 2004, was smaller than 5% and therefore significantly lower than the worst drawdown experienced by passively holding on to the asset and lower than the five worst drawdowns listed above in Table 3.8 for the buy-and-hold long-term bond strategy. Secondly, the time periods in which the ten largest drawdowns are experienced following our *Overall* bond market factor strategy are only covered by two interest rate hike periods—namely, January 2004 until October 2008 and June 2010 until May 2011. However, five out of ten reported drawdowns occur during these periods. Thirdly, none of the three worst drawdown periods in the benchmark strategy are visible in the *Overall* strategy's drawdown table—therefore, applying the *Overall* factor successfully circumvents the periods in which the largest drawdowns are experienced in the underlying asset, and no significant losses occur during these periods. Looking at the worst drawdown of 4.26%, we can identify that this drawdown occurred during a period, in which the passive strategy also experienced drawdowns, including its fourth largest, of 5.15%. While the drawdown length of the *Overall* strategy is significantly longer than that of the buy-and-hold strategy, the factor strategy is able to reduce the drawdown depth by almost 1%, or 17% in relative terms. The second largest drawdown reported in Table 3.9 is 4.21%. We find the same period in the drawdown table of the buy-and-hold strategy in Table 3.8, with a magnitude of 4.58%. While this reduction of 0.37% in absolute and 8% in relative terms seems negligible, it is remarkable as this is the second largest drawdown experienced following the *Overall* factor while it is the fifth largest drawdown reported in Table 3.8. Comparing the fourth largest drawdown, at 3.56%, in Table 3.9 with the drawdown experienced during the same period for the buy-and-hold strategy at a magnitude of 4.41% again supports the strength of our *Overall* bond market factor, reducing the drawdown by 0.8% in absolute and 19% in relative terms. These findings support our aforementioned reasoning on the superior drawdown behavior of the *Overall* bond market factor strategy. To deepen the analysis we now move to the largest drawdowns experienced following the individual factors: cycle, carry, equity market performance, and bond market momentum.

[7] We do not report the drawdown analysis of the *Collection* (*COL*) bond market factor, as the results are similar.

Table 3.9: This table shows the largest drawdowns detected in the active factor strategy *overall* using total return data for the region Switzerland. The tested time period spans from 1999-04-29 until 2017-03-30.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2003-03-12	2003-06-23	2004-12-03	-0.0426	633	104	529
2	2001-11-08	2001-12-28	2002-08-14	-0.0421	280	51	229
3	2015-01-26	2015-06-10		-0.0395	796	136	
4	2007-11-26	2008-04-18	2008-08-20	-0.0356	269	145	124
5	2010-08-25	2010-09-13	2011-07-11	-0.0292	321	20	301
6	2008-10-09	2008-10-14	2008-11-11	-0.0291	34	6	28
7	2009-02-19	2009-02-26	2010-05-06	-0.0217	442	8	434
8	2008-12-08	2009-01-07	2009-01-14	-0.0209	38	31	7
9	2006-09-27	2007-10-16	2007-11-19	-0.0208	419	385	34
10	2001-03-28	2001-04-30	2001-06-26	-0.0201	91	34	57

Factor: Cycle

The three largest discovered drawdowns periods resulting from the cycle factor strategy reported in Table 3.10 overlap with the fifth, seventh, and eighth largest drawdowns in the underlying long-term bond return series, resepectively. While the length of the largest drawdown is 50 days longer than that of the underlying asset, the other two drawdowns display the same drawdown length. Disappointingly, all of these drawdowns are of exactly the same magnitude as those of the buy-and-hold strategy, therefore not adding any protection in terms of drawdown management in these cases. However, the biggest drawdowns reported in the cycle strategy are significantly—up to 50%—lower than those experienced as a buy-and-hold investor. To illustrate this statement, consider the fact that the largest drawdown resulting from the cycle factor is only the fifth largest a buy-and-hold investor experiences. In addition, Table 3.8 reports the fourth largest drawdown in the period 2003-06-12 until 2004-03-08, of 5.15%, while the cycle factor is only hit by a 4.1% drawdown from 2003-03-12 until 2003-06-10, and therefore successfully reduces this drawdown.

Table 3.10: This table shows the largest drawdowns detected in the active factor strategy cycle using total return data for the region Switzerland. The tested time period spans from 1999-04-29 until 2017-03-30.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2001-11-08	2002-03-08	2002-08-14	-0.0458	280	121	159
2	2008-03-25	2008-06-19	2008-08-13	-0.0441	142	87	55
3	2015-01-26	2015-06-10		-0.0431	796	136	
4	2003-03-12	2003-04-07	2003-06-10	-0.0410	91	27	64
5	2009-02-19	2009-05-28	2011-06-10	-0.0317	842	99	743
6	2008-10-09	2008-10-14	2008-11-11	-0.0291	34	6	28
7	2008-02-06	2008-02-27	2008-03-21	-0.0244	45	22	23
8	2003-06-12	2003-06-23	2004-11-23	-0.0240	531	12	519
9	2008-12-08	2009-01-07	2009-01-14	-0.0209	38	31	7
10	2001-03-28	2001-04-30	2001-06-26	-0.0201	91	34	57

Factor: Carry

Six out of ten drawdowns reported for our carry strategy occur during the three major periods of rising interest rates. Our first observation upon looking at Table 3.11 is that the largest drawdown experienced when following the carry strategy is smaller than the four largest observed in the underlying asset. With a magnitude of 4.62%, the largest drawdown reported for the carry factor occurs during the second major prolonged period of rising interest rates. During the same period, the buy-and-hold investor lost 6.62%—2% more in absolute terms and more than 30% more in relative terms. Also, the period in which the second largest drawdown for the carry strategy occurs overlaps with a drawdown period reported for the buy-and-hold strategy as shown in Table 3.8—resulting in its largest loss, of 9.24%. In contrast, the carry factor strategy loses only 4.14%—a reduction of 5% on an absolute basis or 55% in relative terms. Moving down the list to the third largest drawdown reported in Table 3.11, we recognize a loss of 3.64% during the period of June 2003 to November 2004. The underlying asset, however, loses significantly more, with a reported drawdown of 5.15%. Again, this is a reduction of more than 1.5% in absolute terms and almost 30% on a relative basis.

Table 3.11: This table shows the largest drawdowns detected in the active factor strategy carry using total return data for the region Switzerland. The tested time period spans from 1999-04-29 until 2017-03-30.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2006-09-27	2008-04-18	2008-09-29	-0.0462	734	570	164
2	1999-04-30	2000-05-19	2000-12-15	-0.0414	596	386	210
3	2003-06-12	2004-04-26	2004-11-11	-0.0364	519	320	199
4	2010-08-25	2010-09-13	2011-08-05	-0.0292	346	20	326
5	2008-10-09	2008-10-14	2008-12-03	-0.0291	56	6	50
6	2005-09-23	2006-06-26	2006-09-25	-0.0271	368	277	91
7	2001-11-08	2001-11-27	2002-06-10	-0.0241	215	20	195
8	2015-02-03	2015-06-10	2016-02-18	-0.0232	381	128	253
9	2012-12-11	2013-10-16	2014-01-31	-0.0203	417	310	107
10	2002-07-25	2002-10-15	2002-12-06	-0.0202	135	83	52

Factor: Equity Market Performance

The equity market performance factor is the only factor that experiences a drawdown of larger than 5%, with one of 6%. The aforementioned drawdown occurs between July 1999 and January 2001, which is also when the largest drawdown of the underlying is observed. The latter, however, has a magnitude of 9.24% and is therefore 3.24%, or in relative terms 35%, larger. The equity market performance factor clearly reduces this by entering the drawdown period three months later. This drawdown period overlaps also with the first reported period of rising interest rates. The longest period of interest rate hikes ran from January 2004 to October 2010. Clearly, the second, third, seventh, and ninth largest drawdowns occurred during this period. In this period, we also report the second largest drawdown for the underlying total return series, of 6.62%. While the equities factor experiences the second largest drawdown with a performance impact of 4.52%, its duration—over 1,200 days—is remarkably long. The third largest drawdown reported during the period from March 2008 to August 2008 generates a loss of 4.34%, which is slightly less than the drawdown experienced by the buy-and-hold investor during the very same period, with an impact of 4.41%. However, it is again important to keep in mind that while this drawdown of 4.34% is only slightly less than the one experienced as a buy-and-hold investor, it is the third largest resulting from employing the factor strategy—whereas compared to the buy-and-hold investment strategy it is only the seventh largest reported loss.

Factor: Bond Market Momentum

Table 3.12: This table shows the largest drawdowns detected in the active factor strategy equities using total return data for the region Switzerland. The tested time period spans from 1999-04-29 until 2017-03-30.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1999-07-23	1999-10-14	2001-01-05	-0.0600	533	84	449
2	2003-03-12	2004-06-29	2006-08-22	-0.0452	1260	476	784
3	2008-03-25	2008-06-19	2008-08-13	-0.0434	142	87	55
4	2001-11-08	2002-07-05	2002-09-16	-0.0424	313	240	73
5	2012-08-03	2013-09-10	2014-01-21	-0.0338	537	404	133
6	2010-08-25	2011-04-11	2011-07-29	-0.0296	339	230	109
7	2008-10-09	2008-10-14	2008-11-11	-0.0291	34	6	28
8	2015-01-26	2015-02-18	2015-10-21	-0.0287	269	24	245
9	2008-02-06	2008-02-27	2008-03-21	-0.0244	45	22	23
10	2015-12-02	2015-12-30	2016-02-29	-0.0240	90	29	61

Following the bond market momentum factor as a bond investment strategy implies a maximum drawdown of 4.84% during the period June 2012 until November 2011. The detected drawdown is therefore larger than the one reported in the buy-and-hold strategy for a similar time period—namely, from December 2012 to May 2014. The bond market momentum factor, which adjusts its signals slowly due to a lookback period of four months, amplifies the drawdown as it starts losing money earlier and does so for a longer time period. The same is true for the second largest drawdown reported in Table 3.13, where the bond market momentum signal is again lagging and therefore losing money for too long. Interestingly, only drawdowns number 5, 6, 7, and 10 occur during the three sustained periods of rising interest rates. Bond market momentum, therefore, is able to reduce the worst drawdowns experienced by the buy-and-hold investor, but fails to completely convince in certain periods of rising interest rates.

Table 3.13: This table shows the largest drawdowns detected in the active factor strategy bond market momentum using total return data for the region Switzerland. The tested time period spans from 1999-04-29 until 2017-03-30.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2012-06-01	2014-02-12	2014-11-28	-0.0484	911	622	289
2	2003-03-12	2003-06-23	2004-12-08	-0.0423	638	104	534
3	2015-01-26	2015-06-10		-0.0395	796	136	
4	2009-02-19	2009-09-10	2010-02-10	-0.0333	357	204	153
5	2010-08-25	2010-09-13	2011-07-11	-0.0292	321	20	301
6	2008-10-09	2008-10-14	2008-11-11	-0.0291	34	6	28
7	2007-11-26	2008-02-27	2008-09-05	-0.0284	285	94	191
8	2001-11-08	2001-11-27	2002-06-26	-0.0241	231	20	211
9	2008-12-08	2009-01-07	2009-01-14	-0.0209	38	31	7
10	2006-11-21	2007-10-16	2007-11-19	-0.0204	364	330	34

3.7 Additional Results

In the appendix of this paper in Chapter C we report additional results of our backtests. While we report the results for the Swiss and global sovereign bond market in the main paper, we provide the empirical results of our market timing and duration switching strategy for Australia, Canada, Germany, Japan, the UK, and the USA. As for our main results, the market timing strategy shows superior results in terms of Sharpe ratio based on the *Overall* factor for most countries. While Japan and Germany show the most promising results, we find the worst results for Australia and Canada. From an individual factor perspective momentum appears to be best performing factor, generating the highest Sharpe ratio across all tested countries for both, long- and short-duration bonds. The worst performing individual factors for the long-duration market timing strategies are carry and equities. On the short-duration side, we find the cycle factor to be one of the worst performing indicators. Similar to the main results, the experienced maximum drawdown can also be significantly reduced relative to the passive buy-and-hold strategy by following our *Overall* factor signal. For the duration switching strategy, we get results supporting our main findings for Germany, the UK, the USA, Japan, and Canada—namely, higher Sharpe ratios generated by the *Overall* factor strategy relative to the buy-and-hold strategy. However, we report a lower Sharpe ratio for Australia following the *Overall* factor. Momentum appears to be the best individual factor, generating the highest Sharpe ratio in four out of six backtests, with carry being the best performing individual factor in the remaining two backtests. Also in line with our main results are the findings in the analysis of drawdowns: investing according to the *Overall* factor yields a significant reduction in experienced drawdowns. Not only does the *Overall* factor reduce the maximum drawdown, but—on average—reports a lower maximum drawdown than the largest 3–5 drawdowns observed in the underlying asset. The *Overall* factor which shows the worst results for Australia and Canada reduces the maximum drawdown by 56% and and 64%, respectively. On top, the experienced maximum drawdowns resulting from the *Overall* factor for Australia is less than the four largest detected drawdowns in the underlying asset, and in the Canadian case it has the same magnitude as the sixth largest drawdown reported for the buy-and-hold strategy. The *Overall* factor for Japan—the outstanding performer of our above mentioned backtests—experiences a maximum drawdown of 2.77%, while the buy-and-hold investor suffers a maximum drawdown of more than 10%. The experienced loss of 2.77% is less than the 11th largest drawdown experienced by the passive buy-and-hold investor.

3.8 Conclusion

In this paper we develop a bond market factor for Swiss sovereign bonds to guide the duration discussion in asset allocation committees but also to support the asset allocation decision between bonds and cash. We construct Swiss and global bond market factors that extend Morgan Stanley's universe of bond market factors. Using four region-specific individual factors, we build an equally weighted *Overall* factor to signal whether investments in the respective sovereign bond market are attractive or whether we should reduce risk by either moving into cash or reducing the duration. In our empirical analysis, we show that our sovereign bond market factor is able to beat holding cash as well as the static buy-and-hold strategy by employing an active bond market investment strategy, thereby improving each region's Sharpe ratio, annualized standard deviation, and maximum drawdown. To do so, we test two active bond market strategies: we call the first the "market timing strategy", in which we are invested in the same duration bonds as in the buy-and-hold strategy, but exit trades once the respective bond market factor signals us to do so and accordingly move to cash. The "duration switching strategy" is our second strategy, in which we are invested in long-duration bonds if the market for bonds is attractive, but move to short-duration bonds if the environment for bonds is worsening. In terms of risk taking, the "duration switching strategy" is clearly more aggressive than the "market timing strategy", as the investor is still exposed to bond market risks even if circumstances worsen. The empirical results of our study are in line with this economic reasoning; the "duration switcher" is able to generate higher returns accompanied by higher experienced volatility. However, the higher returns compensate the increase in volatility, resulting in a higher Sharpe ratio compared to the "market timing strategy". While we also report better Sortino and modified Burke ratios for the duration switching strategy, the market timing strategy shows superior results in terms of the Bernardo and Ledoit and Calmar ratios. Even though the drawdown experienced in the duration switching strategy is higher than that of the market timing strategy, the relatively higher return generated by the duration switching strategy overcompensates this, resulting in a slightly higher Sortino ratio. As the modified Burke ratio is also connected to the drawdowns experienced, the same reasoning can be applied to explain the inferiority of the market timing strategy. On the other hand, the Bernardo and Ledoit ratio, which captures the ratio of positive to negative returns, favors the market timing strategy. As the market timing strategy sells all bond holdings once the bond market factor indicates a bad environment for bond investments and moves entirely into cash, the denominator of this performance metric is smaller, yielding superior results relative to the duration switching strategy, which is always exposed to bond market risks. The superior results for the market timing strategy in terms of the Calmar ratio are a result of the lower maximum drawdown experienced by this strategy. Again, this does not come as a surprise as the market timing strategy is allowed to leave the bond market completely, while the duration switching strategy can only reduce bond market risk by lowering the portfolio duration. However, we have to keep in mind that over recent years interest rates have been falling constantly, and therefore that being invested in short-duration bonds did not pay off relative to taking more interest rate risk by being invested in long-duration bonds. This fact is also reflected in the lower Sharpe ratio achieved by the passive buy-and-hold strategy for short-term Swiss sovereign bonds compared to their longer-term counterparts. Generally, falling interest rates are also reported in our extended analysis on drawdown behavior, where we find that our *Overall* strategy outperforms the buy-and-hold strategy in times of rising interest rates, therefore anticipating the negative impact on bond portfolios. Overall, we find that not only the final bond market factor strategy but also the individual input factors outperform the buy-and-hold strategy in their drawdown behavior, avoiding the largest losses experienced when following the buy-and-hold approach and therefore reducing the drawdown figures significantly.

Acknowledgments

I would like to thank my advisor Karl Schmedders for his support and guidance in this project. I would also like to thank Malte Schumacher and the research department of OLZ & Partners Asset and Liability Management AG, particularly Lorenz Beyeler and Cyril Bachelard, for their extensive review and feedback, as well as the conferences audiences at the 2018 World Finance and Banking Symposium, the 2018 World Finance Conference, and the 25^{th} International Conference on Quantitative Finance—"Forecasting Financial Markets"—at the Oxford-Man Institute at the University of Oxford.

C Appendix: Chapter 3

This appendix contains the additional results from our empirical backtests. While the main paper focuses on the Swiss and global sovereign bond market factors, this appendix contains the results for the countries Germany, the UK, the USA, Japan, Australia, and Canada. We first present the data used in the empirical backtests in Section C.1, followed by Section C.2 which is again split into the three analyses presented in the main paper: The results for the market timing strategy are presented in Subsection C.2.1, the duration switching strategy results are reported in Subsection C.2.2, and the in-depth duration analysis is presented in Subsection C.2.3.

C.1 Data

Table C.1: This table lists the principal and total return series used for our empirical analysis. The data is collected from the Bloomberg Professional Terminal and is calculated by Citigroup. For every country we collect short- (3-5 year) and long-term (7-10 year) bond series. Every bond series is in local currency.

Series Name	**Region**	**Currency**	**First Date**
Citigroup GBI Australia 3–5 Year	Asia	AUD	1987-07-31
Citigroup GBI Australia 7–10 Year	Asia	AUD	1987-07-31
Citigroup GBI Canada 3–5 Year	North America	CAD	1987-07-31
Citigroup GBI Canada 7–10 Year	North America	CAD	1987-07-31
Citigroup GBI Germany 3–5 Year	Europe	EUR	1987-07-31
Citigroup GBI Germany 7–10 Year	Europe	EUR	1987-07-31
Citigroup GBI Japan 3–5 Year	Asia	JPY	1987-07-31
Citigroup GBI Japan 7–10 Year	Asia	JPY	1987-07-31
Citigroup GBI Switzerland 3–5 Year	Switzerland	CHF	1999-04-30
Citigroup GBI Switzerland 7–10 Year	Switzerland	CHF	1999-04-30
Citigroup GBI UK 3–5 Year	Europe	GBP	1987-07-31
Citigroup GBI UK 7–10 Year	Europe	GBP	1987-07-31
Citigroup GBI US 3–5 Year	USA	USD	1987-07-31
Citigroup GBI US 7–10 Year	USA	USD	1987-07-31
Citigroup WGBI 7–10 Year Yr USD	World	USD	1994-06-02

Table C.2: This table lists the bond market factors used in our empirical analysis. The data is collected from the Bloomberg Professional Terminal and calculated by Morgan Stanley.

Factor	**Region**	**First Date**
Bond Market Factor Australia Overall⋆	Asia	1993-12-08
Bond Market Factor Australia Business Cycle⋆	Asia	2000-03-02
Bond Market Factor Australia Carry⋆	Asia	1993-05-08
Bond Market Factor Australia Equities⋆	Asia	1993-05-08
Bond Market Factor Australia Momentum⋆	Asia	1993-05-08
Bond Market Factor Canada Overall⋆	North America	1993-05-08
Bond Market Factor Canada Business Cycle⋆	North America	2000-03-08
Bond Market Factor Canada Carry⋆	North America	1993-05-08
Bond Market Factor Canada Equities⋆	North America	1993-05-08
Bond Market Factor Canada Momentum⋆	North America	1993-05-08
Bond Market Factor Germany Overall⋆	Europe	1993-05-08
Bond Market Factor Germany Business Cycle⋆	Europe	2002-08-08
Bond Market Factor Germany Carry⋆	Europe	1993-05-08
Bond Market Factor Germany Equities⋆	Europe	1993-05-08
Bond Market Factor Germany Momentum⋆	Europe	1993-05-08
Bond Market Factor Japan Overall⋆	Asia	1993-05-08
Bond Market Factor Japan Business Cycle⋆	Asia	2002-05-09
Bond Market Factor Japan Carry⋆	Asia	1993-05-08
Bond Market Factor Japan Equities⋆	Asia	1993-05-08
Bond Market Factor Japan Momentum⋆	Asia	1993-05-08
Bond Market Factor UK Overall⋆	Europe	1993-05-08
Bond Market Factor UK Business Cycle⋆	Europe	2002-01-08
Bond Market Factor UK Carry⋆	Europe	1993-05-08
Bond Market Factor UK Equities⋆	Europe	1993-05-08
Bond Market Factor UK Momentum⋆	Europe	1993-05-08
Bond Market Factor US Overall⋆	USA	1994-01-06
Bond Market Factor US Business Cycle⋆	USA	1998-01-01
Bond Market Factor US Carry⋆	USA	1993-05-08
Bond Market Factor US Equities⋆	USA	1993-05-08
Bond Market Factor US Momentum⋆	USA	1993-05-08

C.2 Trading Strategies: Results

This section contains the empirical results for additional countries, based on the data provided by Morgan Stanley.

C.2.1 Market Timing Strategy

While the market timing strategy shows superior results in terms of Sharpe ratio based on the *Overall* factor for Germany, the UK, the USA, and Japan it fails to do so for Australia and Canada. This finding is robust for long- and short-duration bonds. As in the main paper, the improved Sharpe ratio is always a result of a lower volatility relative to the buy-and-hold strategy. Unfortunately, the annual return generated by the *Overall* factor for Australia and Canada is too low, such that the lower volatility is not able to compensate this and therefore, the conducted show a smaller Sharpe ratio relative to the buy-and-hold strategy. Also in line with the main results of the paper are the reported maximum drawdown figures which show a reduction relative to the buy-and-hold strategy in all tests apart from short-duration case for Canada.

Region: Germany

7–10 Years

Table C.3: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Germany. The tested time period spans from 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0370	0.0267	0.0258	0.0269	0.0387	0.0274	0.0337
Ann. Std Dev	0.0425	0.0275	0.0306	0.0285	0.0299	0.0286	0.0268
Ann. Sharpe	0.8701	0.9710	0.8433	0.9415	1.2939	0.9580	1.2578
Max. Drawdown	0.0802	0.0551	0.0802	0.0610	0.0630	0.0464	0.0468
Avg. Drawdown	0.0079	0.0066	0.0065	0.0057	0.0054	0.0067	0.0053
Avg. Length	26.3862	36.7203	30.6274	33.2648	24.9656	34.8551	29.2276
Avg. Recovery	15.7884	17.6780	16.9670	19.2192	15.0219	19.1522	15.6306
Sortino	0.0801	0.0937	0.0776	0.0886	0.1221	0.0907	0.1208
Bernardo & Ledoit	1.1938	1.3696	1.2501	1.3404	1.4058	1.3532	1.4791
Mod. Burke	15.2507	18.5701	14.9525	17.3233	24.4818	17.9916	24.1149
Calmar	0.4609	0.4843	0.3217	0.4404	0.6147	0.5905	0.7197

3–5 Years

Table C.4: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Germany. The tested time period spans from 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0242	0.0156	0.0185	0.0191	0.0256	0.0167	0.0225
Ann. Std Dev	0.0210	0.0143	0.0164	0.0150	0.0159	0.0148	0.0146
Ann. Sharpe	1.1515	1.0909	1.1263	1.2685	1.6093	1.1260	1.5351
Max. Drawdown	0.0435	0.0241	0.0386	0.0323	0.0225	0.0301	0.0301
Avg. Drawdown	0.0035	0.0033	0.0029	0.0030	0.0026	0.0031	0.0026
Avg. Length	20.1701	38.5593	27.5584	30.2939	22.3048	33.7808	26.1181
Avg. Recovery	10.4274	16.9407	14.2080	17.4449	13.8006	17.6781	13.9236
Sortino	0.1075	0.1066	0.1039	0.1229	0.1573	0.1091	0.1525
Bernardo & Ledoit	1.2732	1.4547	1.3513	1.4960	1.5483	1.4514	1.6281
Mod. Burke	20.7448	21.3873	20.1557	24.7621	31.4844	21.9375	30.5930
Calmar	0.5571	0.6448	0.4794	0.5895	1.1384	0.5542	0.7459

Region: UK

7–10 Years

Table C.5: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region UK. The tested time period spans from 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0391	0.0209	0.0251	0.0281	0.0323	0.0304	0.0296
Ann. Std Dev	0.0464	0.0291	0.0352	0.0325	0.0329	0.0350	0.0296
Ann. Sharpe	0.8429	0.7203	0.7141	0.8638	0.9818	0.8671	0.9990
Max. Drawdown	0.0773	0.0622	0.0773	0.1168	0.0531	0.0914	0.0759
Avg. Drawdown	0.0095	0.0088	0.0087	0.0076	0.0077	0.0093	0.0074
Avg. Length	29.8580	63.6875	52.9806	39.7514	37.6359	44.2982	42.9061
Avg. Recovery	17.5089	35.7875	26.3161	21.7680	19.1382	27.4912	24.8619
Sortino	0.0793	0.0681	0.0678	0.0812	0.0932	0.0830	0.0974
Bernardo & Ledoit	1.1855	1.2559	1.2213	1.3137	1.3196	1.2850	1.3990
Mod. Burke	15.1674	13.3094	12.9461	15.8743	18.6008	16.5289	19.7533
Calmar	0.5058	0.3364	0.3248	0.2406	0.6074	0.3325	0.3897

3–5 Years

Table C.6: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region UK. The tested time period spans Avg.BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0299	0.0127	0.0172	0.0198	0.0236	0.0191	0.0196
Ann. Std Dev	0.0224	0.0148	0.0168	0.0164	0.0165	0.0166	0.0146
Ann. Sharpe	1.3353	0.8637	1.0209	1.2073	1.4284	1.1529	1.3411
Max. Drawdown	0.0455	0.0455	0.0344	0.0573	0.0277	0.0317	0.0236
Avg. Drawdown	0.0039	0.0043	0.0040	0.0034	0.0033	0.0039	0.0032
Avg. Length	20.1811	53.0104	39.8689	31.6726	27.7153	35.7571	35.6995
Avg. Recovery	10.7819	27.6979	17.5825	17.6771	16.5104	21.4071	19.8592
Sortino	0.1268	0.0809	0.0977	0.1144	0.1388	0.1133	0.1347
Bernardo & Ledoit	1.3081	1.3153	1.3290	1.4619	1.4964	1.3958	1.5715
Mod. Burke	25.1850	16.2074	19.0032	22.7850	28.2779	23.2294	27.7444
Calmar	0.6569	0.2805	0.5001	0.3457	0.8518	0.6044	0.8278

Region: USA

7–10 Years

Table C.7: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region USA. The tested time period spans 1994-06-02 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0367	0.0186	0.0226	0.0285	0.0369	0.0319	0.0302
Ann. Std Dev	0.0539	0.0363	0.0413	0.0367	0.0389	0.0394	0.0346
Ann. Sharpe	0.6815	0.5120	0.5487	0.7773	0.9486	0.8086	0.8743
Max. Drawdown	0.1056	0.0865	0.0900	0.0796	0.0877	0.0753	0.0721
Avg. Drawdown	0.0131	0.0122	0.0135	0.0094	0.0096	0.0112	0.0100
Avg. Length	43.8366	92.4861	40.0000	45.6964	42.4845	60.4732	55.9552
Avg. Recovery	24.4706	59.9444	26.5229	25.3869	24.3351	35.0714	30.0597
Sortino	0.0631	0.0480	0.0509	0.0740	0.0893	0.0754	0.0825
Bernardo & Ledoit	1.1505	1.1717	1.1706	1.2858	1.2900	1.2707	1.3407
Mod. Burke	11.8750	8.9367	9.5797	14.5512	18.0315	14.6490	16.0309
Calmar	0.3477	0.2148	0.2516	0.3582	0.4207	0.4235	0.4190

3–5 Years

Table C.8: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region USA. The tested time period spans 1994-06-02 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0303	0.0138	0.0155	0.0205	0.0265	0.0218	0.0200
Ann. Std Dev	0.0287	0.0193	0.0219	0.0200	0.0213	0.0212	0.0186
Ann. Sharpe	1.0559	0.7141	0.7077	1.0258	1.2399	1.0315	1.0756
Max. Drawdown	0.0502	0.0451	0.0502	0.0454	0.0389	0.0381	0.0346
Avg. Drawdown	0.0055	0.0054	0.0064	0.0046	0.0045	0.0052	0.0048
Avg. Length	27.6894	52.1901	30.2877	35.5833	31.7922	45.5918	44.0307
Avg. Recovery	16.5191	28.7355	17.7945	19.8529	18.2667	29.9524	28.7975
Sortino	0.0987	0.0669	0.0657	0.1000	0.1196	0.0985	0.1045
Bernardo & Ledoit	1.2456	1.2494	1.2331	1.4051	1.4088	1.3724	1.4570
Mod. Burke	19.2536	12.8791	12.7087	20.4964	24.9156	19.9560	21.3670
Calmar	0.6030	0.3055	0.3083	0.4515	0.6806	0.5731	0.5775

Region: Japan

7–10 Years

Table C.9: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Japan. The tested time period spans 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0155	0.0141	0.0221	0.0181	0.0246	0.0156	0.0228
Ann. Std Dev	0.0278	0.0156	0.0224	0.0207	0.0223	0.0166	0.0189
Ann. Sharpe	0.5573	0.9046	0.9885	0.8785	1.1034	0.9422	1.2044
Max. Drawdown	0.0877	0.0277	0.0570	0.0586	0.0486	0.0364	0.0277
Avg. Drawdown	0.0044	0.0034	0.0043	0.0042	0.0041	0.0032	0.0037
Avg. Length	29.7904	30.8295	22.1875	40.4392	30.5687	30.1793	29.3917
Avg. Recovery	20.1497	18.5194	12.2000	23.9048	17.1145	14.4828	14.8250
Sortino	0.0497	0.0863	0.0934	0.0832	0.1043	0.0875	0.1181
Bernardo & Ledoit	1.1327	1.3689	1.3301	1.3559	1.3725	1.3562	1.5147
Mod. Burke	9.6802	18.1863	18.7665	16.8479	20.7461	18.0792	24.6051
Calmar	0.1763	0.5107	0.3881	0.3096	0.5068	0.4299	0.8225

3–5 Years

Table C.10: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Japan. The tested time period spans 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0059	0.0047	0.0104	0.0092	0.0111	0.0049	0.0105
Ann. Std Dev	0.0101	0.0059	0.0106	0.0092	0.0100	0.0062	0.0088
Ann. Sharpe	0.5869	0.8061	0.9832	1.0005	1.1126	0.7945	1.1960
Max. Drawdown	0.0276	0.0099	0.0322	0.0186	0.0243	0.0147	0.0166
Avg. Drawdown	0.0015	0.0013	0.0019	0.0019	0.0018	0.0012	0.0017
Avg. Length	26.5519	31.0154	33.5244	38.5200	31.6747	38.6357	34.1279
Avg. Recovery	16.9235	15.7692	16.7156	22.0450	19.0964	24.2636	17.6393
Sortino	0.0528	0.0767	0.0948	0.1025	0.1107	0.0759	0.1245
Bernardo & Ledoit	1.1503	1.3481	1.3779	1.4601	1.4304	1.3352	1.5918
Mod. Burke	10.1377	16.0612	18.9972	20.3622	21.8399	15.2338	25.3210
Calmar	0.2149	0.4785	0.3219	0.4956	0.4571	0.3362	0.6363

Region: Australia

7–10 Years

Table C.11: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Australia. The tested time period spans 1993-08-13 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0455	0.0226	0.0146	0.0311	0.0304	0.0159	0.0158
Ann. Std Dev	0.0542	0.0349	0.0303	0.0411	0.0364	0.0317	0.0282
Ann. Sharpe	0.8403	0.6467	0.4818	0.7563	0.8335	0.4998	0.5597
Max. Drawdown	0.1054	0.0775	0.1054	0.1311	0.0595	0.0720	0.0720
Avg. Drawdown	0.0102	0.0108	0.0103	0.0094	0.0097	0.0116	0.0097
Avg. Length	26.5721	59.5312	47.5000	39.4456	48.9172	82.5278	75.3299
Avg. Recovery	13.5631	34.5833	31.9773	23.0259	26.7515	26.5833	24.4845
Sortino	0.0789	0.0619	0.0458	0.0723	0.0804	0.0474	0.0540
Bernardo & Ledoit	1.1846	1.2391	1.2086	1.2680	1.3071	1.2171	1.2758
Mod. Burke	15.4982	12.4879	8.9701	14.6142	16.9841	9.4295	10.8185
Calmar	0.4317	0.2914	0.1386	0.2371	0.5098	0.2202	0.2193

3–5 Years

Table C.12: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Australia. The tested time period spans 1993-08-13 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0397	0.0184	0.0104	0.0249	0.0243	0.0123	0.0115
Ann. Std Dev	0.0279	0.0181	0.0152	0.0222	0.0198	0.0163	0.0149
Ann. Sharpe	1.4256	1.0117	0.6836	1.1194	1.2262	0.7556	0.7724
Max. Drawdown	0.0539	0.0273	0.0539	0.0593	0.0268	0.0262	0.0338
Avg. Drawdown	0.0041	0.0046	0.0047	0.0044	0.0039	0.0045	0.0041
Avg. Length	18.0769	43.4882	62.2667	30.0615	32.5830	60.7423	59.2051
Avg. Recovery	9.7949	27.1102	16.1905	17.0164	19.3036	22.0928	18.0940
Sortino	0.1375	0.1007	0.0660	0.1110	0.1251	0.0747	0.0779
Bernardo & Ledoit	1.3338	1.4037	1.3134	1.4306	1.5035	1.3496	1.4097
Mod. Burke	27.2063	20.6611	13.1717	22.8139	26.5486	15.1265	15.7329
Calmar	0.7374	0.6732	0.1927	0.4192	0.9070	0.4707	0.3407

Region: Canada

7–10 Years

Table C.13: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Canada. The tested time period spans 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0396	0.0203	0.0270	0.0176	0.0389	0.0280	0.0263
Ann. Std Dev	0.0438	0.0307	0.0346	0.0317	0.0344	0.0319	0.0294
Ann. Sharpe	0.9036	0.6625	0.7815	0.5557	1.1304	0.8757	0.8964
Max. Drawdown	0.0721	0.0542	0.0685	0.1217	0.0660	0.0592	0.0535
Avg. Drawdown	0.0090	0.0102	0.0091	0.0103	0.0076	0.0078	0.0082
Avg. Length	28.6482	61.9891	48.6250	64.1311	33.4221	40.5809	50.4367
Avg. Recovery	16.2663	33.7065	28.5417	32.6803	18.0574	19.9632	28.3544
Sortino	0.0827	0.0621	0.0726	0.0518	0.1076	0.0820	0.0856
Bernardo & Ledoit	1.1979	1.2193	1.2426	1.2021	1.3382	1.2857	1.3422
Mod. Burke	15.7161	11.9205	13.7500	10.0939	21.3012	15.9611	16.6460
Calmar	0.5498	0.3751	0.3948	0.1448	0.5903	0.4720	0.4920

3–5 Years

Table C.14: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Canada. The tested time period spans 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0302	0.0160	0.0197	0.0134	0.0291	0.0195	0.0185
Ann. Std Dev	0.0227	0.0162	0.0192	0.0185	0.0198	0.0169	0.0165
Ann. Sharpe	1.3284	0.9854	1.0304	0.7244	1.4745	1.1551	1.1194
Max. Drawdown	0.0321	0.0229	0.0380	0.0831	0.0270	0.0203	0.0330
Avg. Drawdown	0.0040	0.0044	0.0044	0.0047	0.0040	0.0039	0.0043
Avg. Length	22.3589	47.2437	39.7980	51.1689	29.1715	35.7484	40.7797
Avg. Recovery	11.3468	22.2101	22.2857	30.1892	16.2299	19.0000	21.7514
Sortino	0.1246	0.0952	0.0966	0.0676	0.1468	0.1130	0.1109
Bernardo & Ledoit	1.3123	1.3540	1.3411	1.2876	1.4848	1.4060	1.4655
Mod. Burke	24.0873	19.1888	18.6921	13.6739	29.4390	22.6923	22.1154
Calmar	0.9402	0.6975	0.5190	0.1609	1.0799	0.9622	0.5603

C.2.2 Duration Switching Strategy

While the duration switching strategy shows superior results in terms of Sharpe ratio based on the *Overall* factor for Germany, the UK, the USA, Japan, and Canada it fails to do so for Australia. In line with the main results of the paper and the results presened in Section C.2.1 are the reported maximum drawdown figures which show a reduction relative to the buy-and-hold strategy for all countries apart from Canada. Based on the country-specific *Overall* factor, each country reports lower annualized volatility which results in the aforementioned higher Sharpe ratio, overcompensation the reduction in annualied return. Interestingly, Japan's *Overall* factor generates a higher annualized return than the buy-and-hold strategy, resulting in a strong beat on Sharpe ratio level.

Region: Germany

Table C.15: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Germany. The tested time period spans 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	CYC	CRY	EQY	MOM	COL	OVL
Ann. Return	0.0370	0.0326	0.0309	0.0357	0.0413	0.0280	0.0332
Ann. Std Dev	0.0425	0.0305	0.0324	0.0313	0.0323	0.0301	0.0280
Ann. Sharpe	0.8701	1.0684	0.9558	1.1415	1.2780	0.9292	1.1845
Max. Drawdown	0.0802	0.0468	0.0802	0.0622	0.0573	0.0557	0.0590
Avg. Drawdown	0.0079	0.0058	0.0061	0.0051	0.0054	0.0062	0.0051
Avg. Length	26.3862	25.3316	27.9964	22.9911	23.3109	32.3922	28.6691
Avg. Recovery	15.7884	13.3575	15.4493	14.1627	13.6041	17.2092	13.1434
Sortino	0.0801	0.1016	0.0877	0.1061	0.1190	0.0874	0.1124
Bernardo & Ledoit	1.1938	1.2926	1.2455	1.3085	1.3241	1.2815	1.3782
Mod. Burke	15.2507	19.9118	17.0093	20.7253	23.5797	17.2508	22.3661
Calmar	0.4609	0.6967	0.3857	0.5739	0.7207	0.5019	0.5631

Region: UK

Table C.16: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region UK. The tested time period spans 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	CYC	CRY	EQY	MOM	COL	OVL
Ann. Return	0.0391	0.0332	0.0435	0.0391	0.0350	0.0328	0.0350
Ann. Std Dev	0.0464	0.0324	0.0381	0.0355	0.0356	0.0357	0.0314
Ann. Sharpe	0.8429	1.0262	1.1433	1.1016	0.9845	0.9181	1.1157
Max. Drawdown	0.0773	0.0622	0.0773	0.1168	0.0744	0.0903	0.0748
Avg. Drawdown	0.0095	0.0064	0.0057	0.0060	0.0081	0.0083	0.0067
Avg. Length	29.8580	29.6786	21.3025	23.1681	36.1333	34.7214	30.7126
Avg. Recovery	17.5089	15.0774	11.8375	13.8997	18.6400	19.4429	18.3320
Sortino	0.0793	0.0969	0.1069	0.1026	0.0920	0.0877	0.1076
Bernardo & Ledoit	1.1855	1.2737	1.2863	1.2999	1.2559	1.2760	1.3691
Mod. Burke	15.1674	19.0331	20.8221	20.2151	18.2319	17.4521	21.8660
Calmar	0.5058	0.5337	0.5632	0.3352	0.4706	0.3630	0.4675

Region: USA

Table C.17: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region USA. The tested time period spans 1994-06-02 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0367	0.0313	0.0397	0.0351	0.0382	0.0349	0.0333
Ann. Std Dev	0.0539	0.0403	0.0448	0.0406	0.0419	0.0409	0.0361
Ann. Sharpe	0.6815	0.7767	0.8875	0.8651	0.9131	0.8543	0.9212
Max. Drawdown	0.1056	0.0908	0.0900	0.0813	0.0938	0.0926	0.0928
Avg. Drawdown	0.0131	0.0105	0.0078	0.0089	0.0101	0.0108	0.0095
Avg. Length	43.8366	47.4500	28.2790	35.3568	41.7360	53.5120	46.2699
Avg. Recovery	24.4706	27.4500	17.6413	21.0000	22.2487	32.7280	23.8160
Sortino	0.0631	0.0721	0.0814	0.0813	0.0851	0.0793	0.0864
Bernardo & Ledoit	1.1505	1.2028	1.2166	1.2344	1.2330	1.2489	1.3027
Mod. Burke	11.8750	13.7111	15.6847	15.8623	17.0466	15.4317	16.8553
Calmar	0.3477	0.3442	0.4414	0.4315	0.4075	0.3772	0.3588

Region: Japan

Table C.18: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Japan. The tested time period spans 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	**CYC**	**CRY**	**EQY**	**MOM**	**COL**	**OVL**
Ann. Return	0.0155	0.0135	0.0239	0.0209	0.0256	0.0150	0.0225
Ann. Std Dev	0.0278	0.0168	0.0242	0.0229	0.0242	0.0176	0.0206
Ann. Sharpe	0.5573	0.8075	0.9866	0.9163	1.0589	0.8492	1.0925
Max. Drawdown	0.0877	0.0325	0.0570	0.0656	0.0583	0.0361	0.0324
Avg. Drawdown	0.0044	0.0031	0.0039	0.0041	0.0044	0.0033	0.0040
Avg. Length	29.7904	25.9553	24.3668	31.8153	28.0599	31.1935	30.3571
Avg. Recovery	20.1497	13.1732	16.5486	21.9799	16.8521	18.0065	17.1032
Sortino	0.0497	0.0757	0.0918	0.0849	0.0984	0.0779	0.1039
Bernardo & Ledoit	1.1327	1.2545	1.2677	1.2728	1.2959	1.2689	1.3846
Mod. Burke	9.6802	15.6031	18.2687	17.0281	19.5307	15.8713	21.4075
Calmar	0.1763	0.4162	0.4195	0.3194	0.4397	0.4148	0.6952

Region: Australia

Table C.19: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Australia. The tested time period spans 1993-08-13 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	CYC	CRY	EQY	MOM	COL	OVL
Ann. Return	0.0455	0.0347	0.0414	0.0435	0.0382	0.0271	0.0226
Ann. Std Dev	0.0542	0.0387	0.0392	0.0449	0.0402	0.0350	0.0330
Ann. Sharpe	0.8403	0.8967	1.0574	0.9684	0.9498	0.7739	0.6859
Max. Drawdown	0.1054	0.0806	0.1054	0.1415	0.0857	0.0611	0.0758
Avg. Drawdown	0.0102	0.0078	0.0057	0.0077	0.0090	0.0078	0.0082
Avg. Length	26.5721	29.5795	20.6856	23.3205	35.7074	36.1635	44.3034
Avg. Recovery	13.5631	16.8205	10.7317	13.0504	22.0480	20.2642	25.9213
Sortino	0.0789	0.0849	0.0989	0.0914	0.0898	0.0725	0.0648
Bernardo & Ledoit	1.1846	1.2451	1.2715	1.2582	1.2750	1.2423	1.2357
Mod. Burke	15.4982	16.9981	19.9751	18.5493	19.0108	14.5916	13.1484
Calmar	0.4317	0.4310	0.3927	0.3075	0.4455	0.4439	0.2981

Region: Canada

Table C.20: This table shows the annualized return, standard deviation, and Sharpe ratio as they are the most important performance metrics. They are followed by maximum drawdown information as well as additional performance measures, which are documented in the performance evaluation part of this paper. The table reports the tests for the region Canada. The tested time period spans 1993-08-06 until 2017-05-10. BH = Buy and hold, CYC = cycle, CRY = carry, EQY = equities, MOM = momentum, COL = collection, OVL = overall.

	BH	CYC	CRY	EQY	MOM	COL	OVL
Ann. Return	0.0396	0.0310	0.0395	0.0304	0.0415	0.0316	0.0315
Ann. Std Dev	0.0438	0.0339	0.0386	0.0356	0.0373	0.0333	0.0321
Ann. Sharpe	0.9036	0.9145	1.0231	0.8544	1.1104	0.9495	0.9809
Max. Drawdown	0.0721	0.0506	0.1162	0.1216	0.0995	0.0535	0.0796
Avg. Drawdown	0.0090	0.0077	0.0076	0.0079	0.0081	0.0072	0.0075
Avg. Length	28.6482	33.2047	28.0143	36.1532	30.1231	33.9207	37.0191
Avg. Recovery	16.2663	16.3216	16.5286	19.6712	16.0970	17.2927	21.9139
Sortino	0.0827	0.0847	0.0946	0.0788	0.1041	0.0883	0.0924
Bernardo & Ledoit	1.1979	1.2289	1.2552	1.2273	1.2840	1.2695	1.3113
Mod. Burke	15.7161	16.1700	18.2035	15.3862	20.6889	17.2267	18.2220
Calmar	0.5498	0.6134	0.3402	0.2502	0.4166	0.5907	0.3963

C.2.3 Drawdown Behavior

This part of the appendix reports the worst drawdowns experienced. For every country, we first report the drawdowns detected in the principal return data, and afterwards in the total return data—both for the passive buy-and-hold investor. Afterwards, we compare the drawdowns experienced by holding the long-term bonds with the drawdowns experienced by following the active factor signals. Summarizing the results for the country-specific *Overall* factors, we state that following the bond market factor results in significantly lower drawdowns. Apart from the US-case—where the reduction in maximum drawdown is slightly less convincing—the reduction in maximum drawdown is for every country around 50% relative to the buy-and-hold strategy.

Region: Germany

Principal return

Table C.21: This table shows the largest drawdowns detected in the long-term principal return data for the region Germany. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1999-02-28	2000-02-28	2003-06-18	-0.9789	1572	366	1206
2	1994-01-31	1994-11-29	1996-12-10	-0.9736	1045	303	742
3	2005-07-31	2008-07-30	2009-01-10	-0.9599	1260	1096	164
4	2010-09-30	2011-04-29	2011-09-29	-0.9352	365	212	153
5	2013-05-31	2014-01-30	2014-07-09	-0.7849	405	245	160
6	2003-06-30	2003-12-30	2004-12-17	-0.7619	537	184	353
7	2015-04-30	2015-07-30	2016-03-09	-0.7209	315	92	223
8	2016-03-31	2017-02-27		-0.7125	407	334	
9	2009-04-30	2009-06-29	2010-05-08	-0.6964	374	61	313
10	2012-06-30	2013-02-27	2013-04-24	-0.6028	299	243	56
11	2011-10-31	2011-12-30	2012-01-23	-0.5222	85	61	24
12	1997-03-31	1997-04-29	1997-08-20	-0.4596	143	30	113
13	2009-01-31	2009-02-27	2009-04-12	-0.4259	72	28	44
14	1998-10-31	1998-11-29	1999-01-01	-0.3250	63	30	33
15	2005-02-28	2005-03-30	2005-05-13	-0.3011	75	31	44
16	1996-12-31	1997-01-30	1997-03-04	-0.2494	64	31	33
17	1997-08-31	1997-09-29	1997-10-30	-0.2388	61	30	31
18	2010-07-31	2010-08-30	2010-09-06	-0.2346	38	31	7
19	1998-04-30	1998-05-30	1998-06-22	-0.1706	54	31	23
20	1997-10-31	1997-11-29	1997-12-27	-0.1355	58	30	28

Total return

Table C.22: This table shows the largest drawdowns detected in the long-term total return data for the region Germany. The tested time period spans from 1993-08-06 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1999-04-30	1999-10-25	2000-12-04	-0.0863	585	179	406
2	2010-09-01	2011-04-11	2011-08-01	-0.0802	335	223	112
3	1994-01-13	1994-09-16	1995-04-04	-0.0765	447	247	200
4	2008-03-18	2008-06-19	2008-09-29	-0.0615	196	94	102
5	2015-04-21	2015-06-10	2016-01-29	-0.0610	284	51	233
6	2013-05-03	2013-09-05	2014-04-15	-0.0557	348	126	222
7	2005-09-22	2006-05-12	2007-11-08	-0.0530	778	233	545
8	2003-06-16	2003-09-03	2004-03-05	-0.0503	264	80	184
9	2001-11-08	2002-03-25	2002-07-24	-0.0494	259	138	121
10	2009-03-09	2009-06-05	2009-10-01	-0.0462	207	89	118
11	2016-09-29	2017-03-10		-0.0409	225	163	
12	1996-01-25	1996-03-12	1996-08-02	-0.0400	191	48	143
13	2011-11-10	2011-11-29	2012-01-11	-0.0383	63	20	43
14	2011-09-23	2011-10-14	2011-11-09	-0.0359	48	22	26
15	2012-07-23	2012-09-14	2013-03-18	-0.0352	239	54	185
16	1999-01-27	1999-03-04	1999-04-12	-0.0325	76	37	39
17	1998-10-06	1998-10-12	1998-12-01	-0.0314	57	7	50
18	2003-03-11	2003-03-21	2003-05-13	-0.0312	64	11	53
19	2012-06-06	2012-06-20	2012-07-18	-0.0305	43	15	28
20	2001-03-23	2001-05-25	2001-07-31	-0.0302	131	64	67

Table C.23: This table shows the largest drawdowns detected in the active factor strategy *overall* using total return data for the region Germany. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2013-05-03	2013-10-04	2014-04-15	-0.0468	348	155	193
2	2010-06-09	2011-03-03	2011-06-23	-0.0464	380	268	112
3	2008-02-12	2008-07-23	2008-09-05	-0.0333	207	163	44
4	1998-10-06	1998-10-12	2000-04-05	-0.0314	548	7	541
5	2012-06-06	2012-06-20	2013-04-29	-0.0305	328	15	313
6	2009-01-16	2009-02-19	2009-03-20	-0.0280	64	35	29
7	2003-03-11	2003-03-19	2003-05-21	-0.0277	72	9	63
8	1995-06-07	1995-06-30	1995-09-05	-0.0260	91	24	67
9	2008-10-07	2008-10-14	2008-10-24	-0.0252	18	8	10
10	2016-03-02	2017-04-25		-0.0236	436	420	

Table C.24: This table shows the largest drawdowns detected in the active factor strategy cycle using total return data for the region Germany. The tested time period spans from 2002-08-08 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2009-01-16	2009-06-05	2011-07-11	-0.0551	907	141	766
2	2012-07-23	2013-10-16	2014-05-15	-0.0364	662	451	211
3	2012-06-06	2012-06-20	2012-07-18	-0.0305	43	15	28
4	2008-10-07	2008-10-14	2008-10-24	-0.0252	18	8	10
5	2008-05-12	2008-07-02	2008-08-04	-0.0244	85	52	33
6	2004-03-26	2004-09-03	2004-10-14	-0.0220	203	162	41
7	2003-08-11	2003-09-03	2003-09-23	-0.0219	44	24	20
8	2008-12-04	2008-12-12	2008-12-17	-0.0207	14	9	5
9	2011-09-23	2012-05-22	2012-06-01	-0.0197	253	243	10
10	2006-09-27	2006-11-06	2007-02-28	-0.0194	155	41	114

Table C.25: This table shows the largest drawdowns detected in the active factor strategy carry using total return data for the region Germany. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2010-09-01	2011-04-11	2012-10-19	-0.0802	780	223	557
2	1994-01-13	1994-09-16	1995-04-04	-0.0765	447	247	200
3	1999-04-30	1999-09-15	2001-11-01	-0.0582	917	139	778
4	2001-11-08	2002-07-05	2002-09-02	-0.0522	299	240	59
5	2003-06-16	2003-09-03	2004-03-05	-0.0503	264	80	184
6	2013-04-30	2013-09-05	2014-02-27	-0.0484	304	129	175
7	2009-03-09	2009-06-05	2009-10-01	-0.0462	207	89	118
8	1996-01-25	1996-03-12	1996-08-02	-0.0400	191	48	143
9	2003-03-11	2003-03-21	2003-05-13	-0.0312	64	11	53
10	2004-03-26	2004-05-13	2004-08-06	-0.0299	134	49	85

Table C.26: This table shows the largest drawdowns detected in the active factor strategy equities using total return data for the region Germany. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2003-03-11	2004-05-13	2008-01-23	-0.0610	1780	430	1350
2	1994-02-17	1994-06-20	1995-01-27	-0.0558	345	124	221
3	2008-03-18	2008-06-19	2008-08-15	-0.0441	151	94	57
4	1998-10-06	1999-10-25	2000-06-02	-0.0418	606	385	221
5	2011-09-23	2011-11-29	2012-04-05	-0.0365	196	68	128
6	2010-06-09	2010-12-16	2011-06-10	-0.0349	367	191	176
7	2015-06-02	2015-06-10	2015-08-12	-0.0345	72	9	63
8	2013-05-03	2013-12-27	2014-07-21	-0.0313	445	239	206
9	2012-06-06	2012-06-20	2013-02-26	-0.0305	266	15	251
10	2009-03-09	2009-10-29	2010-05-06	-0.0304	424	235	189

Table C.27: This table shows the largest drawdowns detected in the active factor strategy momentum using total return data for the region Germany. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2011-09-23	2012-02-20	2014-05-15	-0.0630	966	151	815
2	2016-07-11	2017-04-25		-0.0360	305	289	
3	2009-01-16	2009-03-18	2009-07-31	-0.0353	197	62	135
4	1994-07-20	1994-12-13	1995-03-16	-0.0345	240	147	93
5	2008-03-18	2008-07-23	2008-09-05	-0.0340	172	128	44
6	2010-09-01	2010-10-20	2011-06-13	-0.0327	286	50	236
7	2003-06-16	2004-01-02	2004-03-05	-0.0313	264	201	63
8	2015-04-21	2015-07-10	2015-10-27	-0.0292	190	81	109
9	2002-10-01	2002-11-25	2003-01-20	-0.0282	112	56	56
10	2003-03-11	2003-03-19	2003-05-19	-0.0277	70	9	61

Region: UK

Principal return

Table C.28: This table shows the largest drawdowns detected in the long-term principal return data for the region UK. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1999-02-28	2007-07-30	2010-09-17	-0.9958	4220	3075	1145
2	1994-01-31	1994-10-30	1998-09-15	-0.9942	1689	273	1416
3	2012-08-31	2014-01-30	2015-02-21	-0.9636	905	518	387
4	2010-09-30	2011-02-27	2011-08-27	-0.8431	332	151	181
5	2016-09-30	2017-02-27		-0.8328	224	151	
6	2015-02-28	2015-07-30	2016-07-30	-0.8195	519	153	366
7	2012-06-30	2012-07-30	2012-08-24	-0.3646	56	31	25
8	2012-02-29	2012-04-29	2012-06-06	-0.2965	99	61	38
9	1998-10-31	1998-11-29	1998-12-12	-0.2119	43	30	13
10	1993-09-30	1993-10-30	1993-12-03	-0.1824	65	31	34
11	2011-10-31	2011-11-29	2011-12-14	-0.0992	45	30	15

Total return

Table C.29: This table shows the largest drawdowns detected in the long-term total return data for the region UK. The tested time period spans from 1993-08-06 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-01-04	1994-06-01	1995-05-24	-0.1322	506	149	357
2	1999-01-25	1999-10-14	2000-07-21	-0.0849	544	263	281
3	2013-05-03	2013-09-10	2014-10-08	-0.0773	524	131	393
4	2010-10-13	2011-02-09	2011-06-10	-0.0631	241	120	121
5	2003-06-16	2003-11-03	2004-10-08	-0.0626	481	141	340
6	2008-03-25	2008-06-13	2008-08-29	-0.0622	158	81	77
7	2016-08-15	2016-11-18		-0.0598	270	96	
8	2009-03-13	2009-06-11	2010-05-19	-0.0584	433	91	342
9	2015-02-02	2015-06-26	2016-01-20	-0.0553	353	145	208
10	2001-11-13	2002-03-25	2002-07-22	-0.0457	252	133	119
11	2006-12-05	2007-06-22	2007-09-07	-0.0454	277	200	77
12	2009-01-02	2009-02-04	2009-03-05	-0.0436	63	34	29
13	1996-01-19	1996-03-12	1996-07-04	-0.0427	168	54	114
14	1995-06-07	1995-06-29	1995-09-01	-0.0415	87	23	64
15	2006-01-19	2006-05-12	2006-12-04	-0.0398	320	114	206
16	1998-10-06	1998-10-12	1998-11-30	-0.0380	56	7	49
17	2012-08-03	2013-02-13	2013-03-27	-0.0353	237	195	42
18	2001-03-23	2001-07-03	2001-08-13	-0.0348	144	103	41
19	2003-03-11	2003-03-21	2003-05-19	-0.0342	70	11	59
20	2008-10-07	2008-10-14	2008-11-07	-0.0331	32	8	24

Table C.30: This table shows the largest drawdowns detected in the active factor strategy *overall* using total return data for the region UK. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2009-03-23	2010-02-19	2010-06-30	-0.0759	465	334	131
2	2013-05-03	2013-12-05	2014-10-07	-0.0598	523	217	306
3	2009-01-02	2009-02-04	2009-03-06	-0.0436	64	34	30
4	2003-03-11	2003-03-21	2005-05-03	-0.0342	785	11	774
5	2008-10-07	2008-10-14	2008-11-07	-0.0331	32	8	24
6	2010-09-01	2010-10-27	2011-03-16	-0.0305	197	57	140
7	2016-02-12	2017-04-26		-0.0292	455	440	
8	2011-10-05	2011-10-12	2012-04-10	-0.0290	189	8	181
9	1994-03-24	1994-03-29	1995-09-12	-0.0276	538	6	532
10	1996-01-05	1996-03-12	1996-06-21	-0.0248	169	68	101

Table C.31: This table shows the largest drawdowns detected in the active factor strategy cycle using total return data for the region UK. The tested time period spans from 2002-08-01 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2008-03-25	2008-06-13	2008-11-20	-0.0622	241	81	160
2	2012-08-03	2013-12-27	2015-05-08	-0.0482	1009	512	497
3	2006-01-19	2006-06-23	2007-09-14	-0.0447	604	156	448
4	2003-03-11	2003-07-03	2005-04-27	-0.0430	779	115	664
5	2011-08-19	2012-03-16	2012-07-18	-0.0423	335	211	124
6	2009-03-23	2010-02-19	2011-03-10	-0.0368	718	334	384
7	2015-06-02	2015-06-26	2015-07-31	-0.0266	60	25	35
8	2015-10-05	2015-11-09	2016-05-06	-0.0266	215	36	179
9	2005-07-01	2005-10-17	2005-12-20	-0.0237	173	109	64
10	2007-12-06	2007-12-12	2008-01-02	-0.0205	28	7	21

Table C.32: This table shows the largest drawdowns detected in the active factor strategy carry using total return data for the region UK. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2013-05-03	2013-09-10	2014-10-08	-0.0773	524	131	393
2	2010-10-13	2011-02-09	2011-06-10	-0.0631	241	120	121
3	2003-06-16	2003-11-03	2008-11-20	-0.0626	1985	141	1844
4	2009-03-13	2009-06-11	2010-05-19	-0.0584	433	91	342
5	2015-02-02	2015-06-26	2016-01-20	-0.0553	353	145	208
6	2009-01-02	2009-02-04	2009-03-05	-0.0436	63	34	29
7	1996-01-19	1996-03-12	1996-07-04	-0.0427	168	54	114
8	2012-08-03	2013-02-13	2013-03-27	-0.0353	237	195	42
9	2003-03-11	2003-03-21	2003-05-19	-0.0342	70	11	59
10	2001-11-13	2002-05-17	2002-07-11	-0.0323	241	186	55

Table C.33: This table shows the largest drawdowns detected in the active factor strategy equities using total return data for the region UK. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-02-18	1994-06-01	1995-09-01	-0.1168	561	104	457
2	1998-10-06	1999-10-14	2000-05-26	-0.0505	599	374	225
3	2013-04-08	2013-12-27	2014-10-13	-0.0501	554	264	290
4	2003-03-11	2004-06-09	2005-11-16	-0.0457	982	457	525
5	2007-12-06	2008-06-13	2008-08-05	-0.0423	244	191	53
6	2009-03-13	2010-02-19	2010-05-20	-0.0369	434	344	90
7	2016-06-18	2016-11-18		-0.0364	328	154	
8	2008-10-07	2008-10-14	2008-11-07	-0.0331	32	8	24
9	2001-03-23	2001-07-03	2001-08-10	-0.0324	141	103	38
10	2011-10-05	2011-10-12	2012-03-28	-0.0290	176	8	168

Table C.34: This table shows the largest drawdowns detected in the active factor strategy momentum using total return data for the region UK. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-01-04	1994-10-26	1995-05-10	-0.0531	492	296	196
2	2009-03-13	2010-04-07	2010-05-20	-0.0426	434	391	43
3	1995-06-07	1995-07-28	1995-11-27	-0.0425	174	52	122
4	2012-08-03	2013-03-08	2014-04-10	-0.0413	616	218	398
5	2009-01-02	2009-02-26	2009-03-06	-0.0397	64	56	8
6	2011-10-05	2012-03-14	2012-05-30	-0.0386	239	162	77
7	1998-10-06	1998-10-12	1998-12-02	-0.0380	58	7	51
8	2007-12-06	2008-07-21	2008-10-06	-0.0369	306	229	77
9	2008-10-07	2008-10-14	2008-11-19	-0.0331	44	8	36
10	2003-03-11	2003-05-02	2003-06-10	-0.0303	92	53	39

Region: USA

Principal return

Table C.35: This table shows the largest drawdowns detected in the long-term principal return data for the region USA. The tested time period spans from 1994-06-01 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1998-10-31	2000-02-28	2002-09-18	-0.9894	1419	486	933
2	2003-06-30	2006-07-30	2008-12-26	-0.9863	2007	1127	880
3	2009-01-31	2010-01-30	2010-09-24	-0.9554	602	365	237
4	2012-08-31	2014-01-30	2016-07-17	-0.9529	1417	518	899
5	1996-02-29	1997-04-29	1998-09-15	-0.9342	930	426	504
6	2016-08-31	2017-02-27		-0.9002	254	181	
7	2010-09-30	2011-04-29	2011-09-06	-0.8683	342	212	130
8	1994-06-01	1994-12-30	1995-06-02	-0.8048	367	213	154
9	2002-10-31	2002-12-30	2003-06-14	-0.7097	227	61	166
10	2012-02-29	2012-04-29	2012-06-08	-0.6013	101	61	40
11	2011-10-31	2011-11-29	2012-01-17	-0.3888	79	30	49
12	1995-07-31	1995-08-30	1995-11-01	-0.3384	94	31	63
13	2012-06-30	2012-07-30	2012-08-17	-0.1744	49	31	18

Total return

Table C.36: This table shows the largest drawdowns detected in the long-term total return data for the region USA. The tested time period spans from 1994-06-02 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2008-12-19	2009-06-10	2010-06-28	-0.1056	557	174	383
2	1998-10-06	2000-01-21	2000-10-11	-0.0913	737	473	264
3	2013-05-03	2013-09-05	2014-10-15	-0.0900	531	126	405
4	2003-06-16	2003-09-02	2004-10-25	-0.0865	498	79	419
5	2016-07-11	2016-12-16		-0.0834	305	159	
6	2010-10-12	2011-02-08	2011-07-29	-0.0807	291	120	171
7	1996-02-14	1996-05-03	1996-11-05	-0.0692	266	80	186
8	2008-03-18	2008-06-13	2008-09-15	-0.0623	182	88	94
9	2001-11-08	2002-03-14	2002-06-19	-0.0591	224	127	97
10	2015-02-03	2015-06-10	2016-01-29	-0.0529	361	128	233
11	2005-06-28	2006-05-12	2006-09-21	-0.0480	451	319	132
12	2008-09-18	2008-10-15	2008-11-19	-0.0472	63	28	35
13	2011-09-23	2011-10-27	2011-12-19	-0.0461	88	35	53
14	2002-10-10	2002-10-22	2003-02-13	-0.0397	127	13	114
15	2012-02-01	2012-03-19	2012-05-04	-0.0386	94	48	46
16	2007-03-14	2007-06-12	2007-08-01	-0.0386	141	91	50
17	2005-02-10	2005-03-28	2005-05-13	-0.0380	93	47	46
18	1994-06-07	1994-11-07	1995-01-31	-0.0376	239	154	85
19	1996-12-04	1997-04-11	1997-06-06	-0.0356	185	129	56
20	2003-03-11	2003-03-21	2003-05-08	-0.0345	59	11	48

Table C.37: This table shows the largest drawdowns detected in the active factor strategy *overall* using total return data for the region USA. The tested time period spans from 1994-06-01 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2008-12-19	2010-04-23	2010-07-20	-0.0721	579	491	88
2	2013-06-17	2013-12-06	2014-10-14	-0.0632	485	173	312
3	2011-09-23	2011-12-21	2013-06-13	-0.0488	630	90	540
4	2008-09-18	2008-10-15	2008-11-19	-0.0472	63	28	35
5	1998-10-06	1999-08-19	2000-10-12	-0.0423	738	318	420
6	2003-06-16	2004-07-27	2004-09-20	-0.0419	463	408	55
7	2002-10-10	2002-10-22	2003-02-25	-0.0397	139	13	126
8	2003-03-11	2003-03-21	2003-05-14	-0.0345	65	11	54
9	2015-04-06	2015-06-10	2015-07-08	-0.0301	94	66	28
10	2016-02-12	2016-05-18		-0.0296	455	97	

Table C.38: This table shows the largest drawdowns detected in the active factor strategy cycle using total return data for the region USA. The tested time period spans from 1998-01-01 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2003-06-16	2003-09-02	2005-06-01	-0.0865	717	79	638
2	2005-06-28	2007-04-06	2008-11-26	-0.0761	1248	648	600
3	2008-12-19	2010-07-13	2011-06-24	-0.0638	918	572	346
4	1998-10-06	2000-01-21	2000-08-10	-0.0607	675	473	202
5	2001-11-08	2001-12-17	2002-09-19	-0.0585	316	40	276
6	2011-09-23	2011-10-27	2015-05-08	-0.0461	1324	35	1289
7	2002-10-10	2002-10-22	2003-03-31	-0.0397	173	13	160
8	2015-06-02	2015-11-09	2016-01-29	-0.0371	242	161	81
9	2016-02-12	2016-03-11	2016-07-05	-0.0256	145	29	116
10	2011-06-27	2011-07-01	2011-07-19	-0.0243	23	5	18

Table C.39: This table shows the largest drawdowns detected in the active factor strategy carry using total return data for the region USA. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2013-05-03	2013-09-05	2014-10-15	-0.0900	531	126	405
2	2003-06-16	2003-09-02	2004-10-25	-0.0865	498	79	419
3	2010-10-12	2011-02-08	2011-07-29	-0.0807	291	120	171
4	2009-04-16	2009-06-10	2010-05-06	-0.0764	386	56	330
5	2008-03-18	2008-06-13	2008-09-15	-0.0623	182	88	94
6	2001-11-08	2002-03-14	2002-06-19	-0.0591	224	127	97
7	2015-02-03	2015-06-10	2016-01-29	-0.0529	361	128	233
8	2008-09-18	2008-10-15	2008-11-19	-0.0472	63	28	35
9	2016-06-29	2016-12-16		-0.0416	317	171	
10	2011-10-04	2011-10-27	2011-12-16	-0.0407	74	24	50

Table C.40: This table shows the largest drawdowns detected in the active factor strategy equities using total return data for the region USA. The tested time period spans from1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-02-16	1994-05-09	1995-02-15	-0.0796	365	83	282
2	2016-02-12	2016-12-27		-0.0734	455	320	
3	2002-10-10	2004-05-13	2005-04-28	-0.0700	932	582	350
4	1998-10-06	1999-08-10	2000-08-01	-0.0579	666	309	357
5	2008-01-24	2008-06-13	2008-09-04	-0.0550	225	142	83
6	2013-06-07	2013-12-06	2014-10-10	-0.0488	491	183	308
7	2008-09-18	2008-10-15	2008-11-19	-0.0472	63	28	35
8	2011-09-23	2011-12-09	2012-05-30	-0.0463	251	78	173
9	1996-08-13	1997-04-11	1997-09-16	-0.0349	400	242	158
10	2009-01-22	2009-02-09	2009-03-18	-0.0322	56	19	37

Table C.41: This table shows the largest drawdowns detected in the active factor strategy momentum using total return data for the region USA. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1998-10-06	1999-11-29	2000-10-20	-0.0877	746	420	326
2	1993-10-18	1994-12-12	1995-04-20	-0.0755	550	421	129
3	2008-12-19	2009-04-06	2010-05-21	-0.0530	519	109	410
4	1996-02-14	1996-07-08	1996-10-31	-0.0511	261	146	115
5	2008-03-18	2008-07-23	2008-09-15	-0.0476	182	128	54
6	2011-09-23	2011-12-09	2012-06-01	-0.0443	253	78	175
7	2012-07-25	2013-11-12	2014-10-15	-0.0412	813	476	337
8	2010-09-01	2010-11-15	2011-06-01	-0.0390	274	76	198
9	2002-10-10	2002-12-16	2003-03-05	-0.0374	147	68	79
10	2004-03-18	2004-04-05	2004-08-13	-0.0348	149	19	130

Region: Japan

Principal return

Table C.42: This table shows the largest drawdowns detected in the long-term principal return data for the region Japan. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-01-31	1994-09-29	1995-06-11	-0.9538	497	242	255
2	1998-10-31	1999-01-30	2002-09-23	-0.9468	1424	92	1332
3	2003-06-30	2004-08-30	2010-05-21	-0.9308	2518	428	2090
4	1995-12-31	1996-05-30	1996-10-30	-0.6837	305	152	153
5	2016-07-31	2017-02-27		-0.6201	285	212	
6	1995-07-31	1995-09-29	1995-10-27	-0.5979	89	61	28
7	2010-10-31	2011-03-30	2012-01-21	-0.5664	448	151	297
8	2013-04-30	2013-06-29	2014-06-23	-0.5583	420	61	359
9	1997-04-30	1997-06-29	1997-08-15	-0.4751	108	61	47
10	1997-11-30	1998-02-27	1998-05-05	-0.3280	157	90	67
11	1996-12-31	1997-01-30	1997-02-26	-0.3141	58	31	27
12	2015-02-28	2015-07-30	2015-11-29	-0.3074	275	153	122
13	1998-06-30	1998-07-30	1998-09-10	-0.2535	73	31	42
14	1995-10-31	1995-11-29	1995-12-29	-0.2263	60	30	30
15	2012-12-31	2013-01-30	2013-03-13	-0.1868	73	31	42
16	2016-03-31	2016-04-29	2016-07-01	-0.0644	93	30	63
17	1997-02-28	1997-03-30	1997-04-07	-0.0623	39	31	8
18	2012-03-31	2012-04-29	2012-05-06	-0.0546	37	30	7
19	2002-09-30	2002-10-30	2002-11-02	-0.0320	34	31	3
20	2015-11-30	2015-12-30	2016-01-09	-0.0285	41	31	10

Total return

Table C.43: This table shows the largest drawdowns detected in the long-term total return data for the region Japan. The tested time period spans from 1993-08-06 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1998-10-05	1999-02-05	2001-01-11	-0.1073	830	124	706
2	2003-06-13	2003-09-02	2007-08-17	-0.0877	1527	82	1445
3	1994-01-11	1994-08-30	1995-03-23	-0.0773	437	232	205
4	2008-03-18	2008-06-13	2008-12-02	-0.0527	260	88	172
5	1995-07-10	1995-08-16	1995-09-26	-0.0473	79	38	41
6	2013-04-05	2013-05-29	2014-02-28	-0.0395	330	55	275
7	2010-10-07	2011-02-16	2011-08-03	-0.0374	301	133	168
8	1997-04-08	1997-05-28	1997-07-25	-0.0371	109	51	58
9	1995-12-13	1996-02-28	1996-08-16	-0.0344	248	78	170
10	2016-07-29	2017-02-06		-0.0342	287	193	
11	2001-03-22	2001-04-18	2001-06-14	-0.0292	85	28	57
12	2001-06-29	2002-02-07	2002-05-16	-0.0267	322	224	98
13	1996-11-06	1996-11-12	1996-11-28	-0.0229	23	7	16
14	1998-06-03	1998-07-14	1998-08-17	-0.0225	76	42	34
15	2009-01-16	2009-06-11	2009-07-06	-0.0212	172	147	25
16	2015-01-20	2015-06-11	2015-10-22	-0.0209	276	143	133
17	1996-12-06	1997-01-06	1997-01-22	-0.0190	48	32	16
18	1995-10-05	1995-10-25	1995-12-07	-0.0188	64	21	43
19	2002-09-13	2002-09-20	2002-10-15	-0.0183	33	8	25
20	2009-10-07	2009-11-09	2009-11-27	-0.0178	52	34	18

Table C.44: This table shows the largest drawdowns detected in the active factor strategy *overall* using total return data for the region Japan. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1997-04-08	1997-07-15	1997-09-22	-0.0277	168	99	69
2	1995-12-13	1996-03-26	1996-08-28	-0.0251	260	105	155
3	1996-11-06	1996-11-12	1996-11-28	-0.0229	23	7	16
4	1997-12-09	1998-08-13	1998-09-10	-0.0228	276	248	28
5	2008-10-09	2008-10-21	2008-11-21	-0.0219	44	13	31
6	1996-12-06	1997-01-06	1997-01-22	-0.0190	48	32	16
7	1995-10-05	1995-10-25	1995-12-07	-0.0188	64	21	43
8	2009-01-26	2009-09-07	2010-04-27	-0.0187	457	225	232
9	2002-09-13	2002-10-07	2002-12-30	-0.0180	109	25	84
10	1995-07-13	1995-08-02	1995-09-20	-0.0171	70	21	49

Table C.45: This table shows the largest drawdowns detected in the active factor strategy cycle using total return data for the region Japan. The tested time period spans from 2002-09-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2009-01-16	2009-06-11	2011-02-23	-0.0277	769	147	622
2	2005-02-03	2006-07-06	2006-08-28	-0.0226	572	519	53
3	2016-07-29	2016-08-08		-0.0209	287	11	
4	2003-10-10	2003-11-07	2003-12-12	-0.0184	64	29	35
5	2008-01-23	2008-02-21	2008-03-06	-0.0131	44	30	14
6	2004-09-29	2004-10-05	2004-10-21	-0.0128	23	7	16
7	2008-09-01	2008-11-05	2008-11-21	-0.0124	82	66	16
8	2007-12-05	2007-12-11	2008-01-04	-0.0105	31	7	24
9	2011-11-21	2011-11-29	2012-02-14	-0.0104	86	9	77
10	2011-03-16	2011-04-12	2011-04-27	-0.0103	43	28	15

Table C.46: This table shows the largest drawdowns detected in the active factor strategy carry using total return data for the region Japan. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2005-07-01	2006-05-10	2008-01-07	-0.0570	921	314	607
2	2008-03-18	2008-06-13	2008-12-02	-0.0527	260	88	172
3	1995-07-10	1995-08-16	1995-09-26	-0.0473	79	38	41
4	1997-04-08	1997-05-28	1997-07-25	-0.0371	109	51	58
5	1995-12-13	1996-02-28	1996-08-16	-0.0344	248	78	170
6	2010-10-22	2010-12-16	2012-04-23	-0.0313	550	56	494
7	1996-11-06	1996-11-12	1996-11-28	-0.0229	23	7	16
8	2000-08-07	2000-09-06	2000-11-13	-0.0220	99	31	68
9	1996-12-06	1997-01-06	1997-01-22	-0.0190	48	32	16
10	1995-10-05	1995-10-25	1995-12-07	-0.0188	64	21	43

Table C.47: This table shows the largest drawdowns detected in the active factor strategy equities using total return data for the region Japan. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1998-10-05	1998-12-30	2001-01-11	-0.0586	830	87	743
2	2004-05-18	2006-10-18	2008-08-04	-0.0366	1540	884	656
3	1994-07-20	1994-10-07	1995-02-14	-0.0289	210	80	130
4	1996-11-06	1996-11-12	1996-11-28	-0.0229	23	7	16
5	2001-06-29	2001-08-07	2002-07-11	-0.0226	378	40	338
6	1998-06-03	1998-07-14	1998-09-10	-0.0225	100	42	58
7	2008-10-09	2008-10-21	2008-11-21	-0.0219	44	13	31
8	1995-07-10	1995-10-25	1996-03-04	-0.0211	239	108	131
9	1998-01-13	1998-04-03	1998-05-15	-0.0195	123	81	42
10	1996-12-06	1997-01-06	1997-01-22	-0.0190	48	32	16

Table C.48: This table shows the largest drawdowns detected in the active factor strategy momentum using total return data for the region Japan. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-01-11	1994-10-07	1995-03-16	-0.0486	430	270	160
2	1999-05-17	2000-03-27	2001-02-19	-0.0458	645	316	329
3	1995-07-10	1995-07-18	1996-08-29	-0.0262	417	9	408
4	1996-11-06	1996-11-12	1996-11-28	-0.0229	23	7	16
5	2005-07-01	2006-03-15	2006-09-26	-0.0227	453	258	195
6	1997-04-08	1997-06-25	1997-07-24	-0.0220	108	79	29
7	2013-04-05	2013-04-15	2013-10-03	-0.0198	182	11	171
8	2001-03-22	2002-03-11	2002-07-10	-0.0195	476	355	121
9	1998-06-03	1998-07-01	1998-09-10	-0.0192	100	29	71
10	1997-11-06	1998-01-21	1998-05-08	-0.0190	184	77	107

Region: Australia

Principal return

Table C.49: This table shows the largest drawdowns detected in the long-term principal return data for the region Australia. The tested time period spans from 1993-08-12 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-02-28	1994-11-29	1997-08-23	-0.9993	1273	275	998
2	1998-11-30	2008-06-29	2009-01-15	-0.9909	3700	3500	200
3	2009-01-31	2010-04-29	2011-12-20	-0.9746	1054	454	600
4	2012-06-30	2014-01-30	2015-02-16	-0.9543	962	580	382
5	2016-09-30	2017-01-30		-0.8713	224	123	
6	2015-04-30	2015-07-30	2016-07-28	-0.7583	456	92	364
7	1998-06-30	1998-09-29	1998-10-22	-0.6905	115	92	23
8	2012-01-31	2012-04-29	2012-05-25	-0.5032	116	90	26
9	1993-11-30	1993-12-30	1994-02-24	-0.4121	87	31	56
10	1997-11-30	1997-12-30	1998-02-24	-0.3806	87	31	56
11	1993-09-30	1993-10-30	1993-11-20	-0.3351	52	31	21
12	1997-08-31	1997-09-29	1997-10-15	-0.2896	46	30	16
13	1998-04-30	1998-05-30	1998-06-08	-0.2293	40	31	9
14	1998-02-28	1998-03-30	1998-04-12	-0.1506	44	31	13
15	2015-02-28	2015-03-30	2015-04-02	-0.0165	34	31	3

Total return

Table C.50: This table shows the largest drawdowns detected in the long-term total return data for the region Australia. The tested time period spans from 1993-08-13 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-02-01	1994-11-08	1995-09-06	-0.1661	583	281	302
2	2009-01-16	2009-06-19	2010-07-06	-0.1054	537	155	382
3	1998-12-18	2000-01-19	2000-06-02	-0.0874	533	398	135
4	2001-11-09	2002-04-02	2002-08-06	-0.0736	271	145	126
5	2003-06-17	2003-11-10	2004-08-20	-0.0695	431	147	284
6	2012-07-26	2013-12-06	2014-05-21	-0.0648	665	499	166
7	2016-09-01	2017-03-10		-0.0646	253	191	
8	1996-02-14	1996-03-11	1996-07-18	-0.0619	156	27	129
9	2001-03-20	2001-07-04	2001-09-12	-0.0576	177	107	70
10	2015-04-16	2015-06-11	2016-01-20	-0.0513	280	57	223
11	2010-09-01	2010-12-13	2011-05-23	-0.0499	265	104	161
12	2008-03-18	2008-06-16	2008-07-31	-0.0421	136	91	45
13	1997-02-19	1997-04-01	1997-05-23	-0.0409	94	42	52
14	1998-06-02	1998-08-28	1998-09-07	-0.0377	98	88	10
15	2002-09-26	2002-10-22	2002-11-11	-0.0376	47	27	20
16	2011-10-05	2011-10-17	2011-11-16	-0.0365	43	13	30
17	2008-10-09	2008-10-13	2008-10-24	-0.0358	16	5	11
18	2003-03-12	2003-03-20	2003-05-08	-0.0357	58	9	49
19	2012-02-02	2012-03-21	2012-04-10	-0.0342	69	49	20
20	1996-12-04	1997-01-03	1997-02-18	-0.0326	77	31	46

Table C.51: This table shows the largest drawdowns detected in the active factor strategy *overall* using total return data for the region Australia. The tested time period spans from 1993-08-12 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2002-11-04	2008-10-13	2008-12-02	-0.0720	2221	2171	50
2	1997-11-20	2001-04-23	2001-11-02	-0.0676	1444	1251	193
3	2012-06-05	2013-06-24	2014-05-29	-0.0621	724	385	339
4	2016-02-12	2017-04-26		-0.0552	455	440	
5	2009-01-16	2009-07-20	2010-05-11	-0.0382	481	186	295
6	2015-06-02	2015-06-11	2015-07-08	-0.0276	37	10	27
7	2015-08-25	2015-09-17	2016-02-09	-0.0246	169	24	145
8	2011-10-05	2011-11-17	2011-12-15	-0.0236	72	44	28
9	2012-01-17	2012-05-17	2012-05-31	-0.0223	136	122	14
10	2002-08-07	2002-08-20	2002-09-04	-0.0220	29	14	15

Table C.52: This table shows the largest drawdowns detected in the active factor strategy cycle using total return data for the region Australia. The tested time period spans from 2000-02-03 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2012-10-04	2014-02-12	2015-03-19	-0.0775	897	497	400
2	2015-04-16	2015-07-15		-0.0618	757	91	
3	2007-09-11	2008-02-19	2008-09-05	-0.0510	361	162	199
4	2001-03-20	2001-04-23	2001-09-12	-0.0443	177	35	142
5	2012-06-05	2012-08-16	2012-10-03	-0.0407	121	73	48
6	2002-11-15	2003-03-20	2003-05-19	-0.0398	186	126	60
7	2008-09-10	2008-10-13	2008-10-24	-0.0368	45	34	11
8	2009-09-29	2010-04-07	2010-06-30	-0.0298	275	191	84
9	2002-01-15	2002-05-15	2002-08-06	-0.0289	204	121	83
10	2005-09-05	2006-10-24	2007-09-06	-0.0285	732	415	317

Table C.53: This table shows the largest drawdowns detected in the active factor strategy carry using total return data for the region Australia. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2009-01-16	2009-06-19	2010-07-01	-0.1054	532	155	377
2	2013-05-20	2013-12-06	2014-05-15	-0.0565	361	201	160
3	2015-04-16	2015-06-11	2016-02-03	-0.0513	294	57	237
4	2016-11-10	2017-03-10		-0.0445	183	121	
5	2008-10-09	2008-10-13	2008-10-24	-0.0358	16	5	11
6	2001-05-11	2001-09-25	2001-11-01	-0.0340	175	138	37
7	2010-12-02	2011-02-09	2011-03-15	-0.0287	104	70	34
8	2001-11-09	2001-12-27	2002-01-14	-0.0283	67	49	18
9	2008-10-27	2008-11-03	2008-11-13	-0.0282	18	8	10
10	2014-09-01	2014-09-19	2014-10-09	-0.0277	39	19	20

Table C.54: This table shows the largest drawdowns detected in the active factor strategy equities using total return data for the region Australia. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1993-12-01	1994-06-27	1995-09-06	-0.1311	645	209	436
2	2002-09-09	2003-03-20	2005-04-06	-0.0525	941	193	748
3	2013-06-11	2013-06-24	2014-01-30	-0.0520	234	14	220
4	1996-03-05	1996-03-11	1996-07-17	-0.0460	135	7	128
5	1999-01-27	1999-10-27	2000-04-17	-0.0449	447	274	173
6	2001-03-20	2001-04-23	2001-08-28	-0.0443	162	35	127
7	1998-06-02	1998-08-28	1998-09-10	-0.0438	101	88	13
8	2016-11-10	2016-12-02		-0.0436	183	23	
9	2007-11-28	2008-02-19	2008-07-07	-0.0400	223	84	139
10	2011-10-05	2012-03-21	2012-05-16	-0.0394	225	169	56

Table C.55: This table shows the largest drawdowns detected in the active factor strategy momentum using total return data for the region Australia. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2012-07-26	2014-03-24	2014-10-16	-0.0595	813	607	206
2	2003-06-17	2004-04-06	2006-09-25	-0.0511	1197	295	902
3	1996-02-14	1996-05-17	1996-08-02	-0.0487	171	94	77
4	2002-09-26	2002-11-25	2003-05-23	-0.0484	240	61	179
5	1995-06-06	1995-09-25	1996-02-13	-0.0436	253	112	141
6	2000-04-18	2000-10-31	2000-12-15	-0.0376	242	197	45
7	1998-01-13	1998-09-17	2000-03-22	-0.0364	800	248	552
8	2008-10-09	2008-10-13	2008-10-24	-0.0358	16	5	11
9	2015-08-25	2016-01-12	2016-06-09	-0.0326	290	141	149
10	2007-09-11	2008-07-22	2008-08-12	-0.0292	337	316	21

Region: Canada

Principal return

Table C.56: This table shows the largest drawdowns detected in the long-term principal return data for the region Canada. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-02-28	1994-07-30	1996-11-28	-0.9956	1005	153	852
2	1998-10-31	2000-02-28	2003-06-09	-0.9699	1683	486	1197
3	2013-05-31	2014-01-30	2015-01-31	-0.9045	611	245	366
4	2015-02-28	2017-02-27		-0.8981	804	731	
5	2009-04-30	2010-05-30	2011-09-01	-0.8747	855	396	459
6	2005-09-30	2006-07-30	2008-03-08	-0.8418	891	304	587
7	1996-12-31	1997-04-29	1997-08-23	-0.7785	236	120	116
8	2004-04-30	2004-07-30	2005-01-25	-0.7043	271	92	179
9	2003-06-30	2003-08-30	2004-03-18	-0.6381	263	62	201
10	1997-11-30	1998-09-29	1998-10-21	-0.6341	326	304	22
11	2012-08-31	2013-02-27	2013-05-28	-0.5547	271	181	90
12	2008-04-30	2008-07-30	2008-12-19	-0.5330	234	92	142
13	2009-01-31	2009-02-27	2009-04-23	-0.5024	83	28	55
14	1993-09-30	1993-10-30	1994-01-07	-0.4441	100	31	69
15	2012-02-29	2012-04-29	2012-06-19	-0.4357	112	61	51
16	1997-08-31	1997-09-29	1997-11-01	-0.3566	63	30	33
17	2011-10-31	2011-11-29	2011-12-31	-0.3443	62	30	32
18	2005-02-28	2005-04-29	2005-05-24	-0.2435	86	61	25
19	2005-07-31	2005-08-30	2005-09-22	-0.2053	54	31	23
20	2012-06-30	2012-07-30	2012-07-31	-0.0020	32	31	1

Total return

Table C.57: This table shows the largest drawdowns detected in the long-term total return data for the region Canada. The tested time period spans from 1993-08-06 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-01-31	1994-06-21	1995-05-05	-0.1494	460	142	318
2	2013-05-03	2013-09-10	2014-07-16	-0.0721	440	131	309
3	2016-10-01	2016-12-16		-0.0638	223	77	
4	2009-03-20	2009-06-10	2010-06-24	-0.0611	462	83	379
5	1999-04-09	2000-01-21	2000-06-02	-0.0610	421	288	133
6	2003-06-16	2003-08-05	2004-01-20	-0.0535	219	51	168
7	2010-10-12	2011-02-16	2011-06-01	-0.0501	233	128	105
8	2004-03-25	2004-06-14	2004-09-16	-0.0476	176	82	94
9	1996-02-14	1996-03-08	1996-08-01	-0.0469	170	24	146
10	2001-11-08	2002-03-25	2002-07-11	-0.0468	246	138	108
11	2015-02-03	2015-06-10	2015-08-19	-0.0457	198	128	70
12	1997-02-18	1997-04-04	1997-06-06	-0.0424	109	46	63
13	2001-03-23	2001-05-17	2001-08-13	-0.0407	144	56	88
14	1995-07-11	1995-08-01	1995-09-05	-0.0402	57	22	35
15	2007-03-08	2007-06-12	2007-09-07	-0.0384	184	97	87
16	1996-12-02	1997-01-10	1997-02-13	-0.0363	74	40	34
17	2015-08-25	2015-11-09	2016-01-12	-0.0353	141	77	64
18	2009-01-16	2009-02-04	2009-03-18	-0.0353	62	20	42
19	1998-10-06	1998-11-06	1998-12-03	-0.0332	59	32	27
20	2016-02-12	2016-04-26	2016-06-10	-0.0322	120	75	45

Table C.58: This table shows the largest drawdowns detected in the active factor strategy *overall* using total return data for the region Canada. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2003-06-16	2004-07-15	2007-09-07	-0.0535	1545	396	1149
2	1996-12-02	1997-02-06	1997-06-13	-0.0501	194	67	127
3	1996-02-14	1996-07-05	1996-08-09	-0.0445	178	143	35
4	2011-10-05	2013-02-01	2014-02-03	-0.0373	853	486	367
5	2015-02-03	2015-07-10	2015-08-24	-0.0362	203	158	45
6	2009-01-16	2009-02-04	2009-03-18	-0.0353	62	20	42
7	2015-08-25	2015-09-25	2016-01-12	-0.0313	141	32	109
8	2010-09-01	2011-03-30	2011-05-26	-0.0311	268	211	57
9	2001-03-23	2001-04-30	2001-08-17	-0.0311	148	39	109
10	2008-10-07	2008-10-10	2008-11-20	-0.0306	45	4	41

Table C.59: This table shows the largest drawdowns detected in the active factor strategy cycle using total return data for the region Canada. The tested time period spans from 2000-08-03 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	2011-10-05	2013-09-10	2014-11-14	-0.0542	1137	707	430
2	2006-12-04	2007-07-06	2008-08-01	-0.0480	607	215	392
3	2003-06-16	2003-07-29	2004-10-20	-0.0434	493	44	449
4	2010-09-01	2011-03-30	2011-07-29	-0.0390	332	211	121
5	2016-06-29	2017-03-13		-0.0388	317	258	
6	2009-01-16	2009-02-04	2009-03-18	-0.0353	62	20	42
7	2008-10-07	2008-11-13	2008-12-01	-0.0346	56	38	18
8	2015-07-28	2015-12-03	2016-01-13	-0.0327	170	129	41
9	2001-12-05	2002-01-25	2002-07-19	-0.0321	227	52	175
10	2001-03-23	2001-04-30	2001-08-17	-0.0311	148	39	109

Table C.60: This table shows the largest drawdowns detected in the active factor strategy carry using total return data for the region Canada. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-01-31	1996-03-08	1996-08-09	-0.0685	922	768	154
2	2013-05-09	2013-09-10	2014-05-15	-0.0638	372	125	247
3	2009-03-20	2009-06-10	2010-06-24	-0.0611	462	83	379
4	2003-06-16	2003-08-05	2004-01-20	-0.0535	219	51	168
5	2010-10-12	2011-02-16	2011-06-01	-0.0501	233	128	105
6	2004-03-25	2004-06-14	2004-09-16	-0.0476	176	82	94
7	2001-11-08	2002-03-25	2002-07-11	-0.0468	246	138	108
8	1997-02-18	1997-04-04	1997-06-06	-0.0424	109	46	63
9	2001-03-23	2001-05-17	2001-08-13	-0.0407	144	56	88
10	2008-03-18	2008-10-10	2008-11-26	-0.0384	254	207	47

Table C.61: This table shows the largest drawdowns detected in the active factor strategy equities using total return data for the region Canada. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1994-02-18	1995-01-20	1995-11-03	-0.1217	624	337	287
2	2013-05-03	2013-07-05	2014-12-12	-0.0607	589	64	525
3	1998-10-06	1999-10-26	2000-11-30	-0.0561	787	386	401
4	2016-02-12	2017-05-10		-0.0540	455	454	
5	2008-12-30	2010-02-22	2011-06-01	-0.0481	884	420	464
6	2002-09-06	2004-06-14	2006-03-16	-0.0440	1288	648	640
7	2001-03-23	2001-07-05	2001-08-17	-0.0361	148	105	43
8	2011-10-05	2011-10-27	2012-04-10	-0.0314	189	23	166
9	1998-07-09	1998-08-27	1998-09-10	-0.0312	64	50	14
10	2008-10-07	2008-10-10	2008-11-20	-0.0306	45	4	41

Table C.62: This table shows the largest drawdowns detected in the active factor strategy momentum using total return data for the region Canada. The tested time period spans from 1993-08-05 until 2017-05-10.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1998-10-06	1999-12-15	2000-08-07	-0.0660	672	436	236
2	2009-03-20	2010-05-11	2010-08-26	-0.0640	525	418	107
3	2003-06-16	2003-09-11	2004-01-09	-0.0387	208	88	120
4	1996-02-14	1996-04-30	1996-08-01	-0.0378	170	77	93
5	2015-02-03	2015-07-10	2015-08-24	-0.0362	203	158	45
6	2012-07-24	2013-03-11	2014-05-14	-0.0361	660	231	429
7	2011-10-05	2012-04-25	2012-07-12	-0.0339	282	204	78
8	1995-07-11	1995-07-19	1995-09-25	-0.0331	77	9	68
9	2008-03-18	2008-07-23	2008-09-05	-0.0302	172	128	44
10	2002-09-24	2002-12-16	2003-05-16	-0.0284	235	84	151

Part III

Bibliography

Bibliography

Asness, C. S., T. J. Moskowitz, and L. Pedersen (2013): "Value and Momentum Everywhere," *The Journal of Finance*, 68, 929–985.

Bailey, D. H., J. M. Borwein, M. L. de Prado, and Q. J. Zhu (2017): "The probability of backtest overfitting," *The Journal of Computational Finance*, 20, 39–69.

Barone Adesi, G., K. Giannopoulos, and F. Bourgoin (1998): "Don't look back," *Risk*, 11, 100–104.

Barone Adesi, G., K. Giannopoulos, and L. Vosper (1999): "VaR without correlations for portfolios of derivative securities," *The Journal of Futures Markets*, 19, 583–602.

——— (2002): "Backtesting Derivative Portfolios with Filtered Historical Simulation (FHS)," *European Financial Management*, 8, 31–58.

Bernardo, A. E. and O. Ledoit (2000): "Gain, Loss, and Asset Pricing," *The Journal of Political Economy*, 108, 144–172.

Black, F. (1976): "Studies of Stock Price Volatility Changes," *Proceedings of the 1976 Meetings of the American Statistical Association, Business, and Economics Section*, 177–181.

Brock, W., J. Lakonishok, and B. LeBaron (1992): "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns," *The Journal of Finance*, 47, 1731–1764.

Chan, L. K. C., N. Jegadeesh, and J. Lakonishok (1996): "Momentum Strategies," *The Journal of Finance*, 51, 1681–1713.

Chande, T. S. and S. Kroll (1994): *The New Technical Trader: Boost Your Profit by Plugging into the Latest Indicators*, Wiley Finance.

Embrechts, P., C. Klüppelberg, and T. Mikosch (1997): *Modelling Extremal Events for Insurance and Finance*, Springer-Verlag Berlin Heidelberg.

Fama, E. F. (1976): "Forward Rates as Predictors of Future Spot Rates," *The Journal of Financial Economics*, 3, 361–377.

Fama, E. F. and K. R. French (1989): "Business Conditions and Expected Returns on Stocks and Bonds," *The Journal of Financial Economics*, 25, 23–49.

Granger, N., D. Greenig, C. Harvey, S. Rattray, and D. Zou (2014): "The unexpected costs of rebalancing and how to address them," *Man Group plc/AHL Working Paper*.

Hansen, P. R. and A. Lunde (2005): "A forecast comparison of volatility models: does anything beat a GARCH(1,1)?" *The Journal of Applied Econometrics*, 20, 873–889.

Harvey, C. R. and Y. Liu (2015): "Backtesting," *The Journal of Portfolio Management*, 42, 13–28.

Harvey, C. R., Y. Liu, and H. Zhu (2016): "... and the Cross-Section of Expected Returns," *The Review of Financial Studies*, 29, 5–68.

Hornbach, M., A. O'Brien, A. Heese, J. Rooth, K. Kawano, and K. Yang (2015): "Our Bond Market Indicators: A Powerful Systematic Approach," Product note, Morgan Stanley.

Hurst, B., Y. H. Ooi, and L. H. Pedersen (2014): "A Century of Evidence on Trend-Following Investing," AQR working paper, AQR Capital Management.

Ilmanen, A. (1995): "Time-Varying Expected Returns in International Bond Markets," *The Journal of Finance*, 50, 481–506.

Jegadeesh, N. and S. Titman (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance*, 48, 65–91.

Kendall, M. (1953): "The Analysis of Economic Time-Series: Prices," *The Journal of the Royal Statistical Society*, 96, 11–25.

Kolanovic, M., N. Panigirtzoglou, J. Normand, L. Bao, and B. Kaplan (2018): "Global Asset Allocation," Global cross-asset strategy, J.P. Morgan.

Korapaty, P. and A. Thakkar (2018): "Yield Curve Inversion," Global markets analyst, Goldman Sachs.

Lambert, D. (1980): "Commodity Channel Index: Tool for Trading Cyclic Trends," *Commodities Magazine*, 1, 120–122.

Lee, C. M. and B. Swaminathan (2000): "Price Momentum and Trading Volume," *The Journal of Finance*, 55, 2017–2070.

Li, W. K. and T. K. Mak (1994): "On the Squared Residual Autocorrelations in Non-linear Time Series with Conditional Heteroscedasticity," *The Journal of Time Series Analysis*, 15, 627–636.

Longin, F. (2000): "From value at risk to stress testing: The extreme value approach," *The Journal of Banking and Finance*, 24, 1097–1130.

Mandelbrot, B. (1963): "Risk-Based Asset Allocation: A New Answer to an Old Question?" *The Journal of Business*, 36, 394–419.

Marshall, B. R., N. N. Nguyen, and N. Visaltanachoti (2014): "Time-Series Momentum versus Moving Average Trading Rules," *SSRN Electronic Journal*.

Mina, J. and J. Y. Xiao (2001): "Return to RiskMetrics: The Evolution of a Standard," *RiskMetrics Group Inc.*

Moskowitz, T. J. and M. Grinblatt (1999): "Do Industries Explain Momentum?" *The Journal of Finance*, 54, 1249–1290.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2012): "Time series momentum," *The Journal of Financial Economics*, 104, 228–250.

Mueller-Glissmann, C., A. Ritzi, I. Wright, and P. Oppenheimer (2018): "The Balanced Bear," Global strategy paper, Goldman Sachs.

Murphy, J. (1999): *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications*, New York Institute of Finance Series, New York Institute of Finance.

Normand, J. (2017): "Investing in an Old Business Cycle with Expensive Markets," Global cross-asset strategy, J.P. Morgan.

Pedersen, L. H. (2010): "Trading on Trends: The Equivalence of TS Momentum, Moving-Average Crossover and Other Filters," AQR working paper, AQR Capital Management.

Posedel, P. (2005): "Properties and Estimation of GARCH(1,1) Model," *Metodoloski zvezki-Advances in Methodology and Statistics*, 2, 243–257.

Rouwenhorst, K. G. (1998): "International Momentum Strategies," *The Journal of Finance*, 53, 267–284.

Sortino, F. A. and L. N. Price (1994): "Performance Measurement in a Downside Risk

Framework," *The Journal of Investing*, 3, 59–64.

Vlaar, P. (2000): "Value at risk models for Dutch bond Portfolios," *The Journal of Banking and Finance*, 24, 1131–1154.

Vlaar, P. and F. Palm (1993): "The Message in Weekly Exchange Rates in the European Monetary System: Mean Reversion, Conditional Heteroscedasticity, and Jumps," *The Journal of Business and Economic Statistics*, 11, 351–360.

Wilder, J. W. (1978): *New Concepts in Technical Trading Systems*, Trend Research.

Zangari, P. (1996): "RiskMetrics - Technical Document," *J.P.Morgan/Reuters*.

Part IV

Curriculum Vitae

Curriculum Vitae

Personal details

Name:	Andreas Thomann
Date of Birth:	October 11, 1987

Education

02/2014 – 04/2019	PhD studies at the Zurich Graduate School of Business, Chair of Quantitative Business Administration University of Zurich, Switzerland
02/2011 – 01/2013	MSc in Business and Economics University of Basel, Switzerland
08/2007 – 01/2011	BA in Business and Economics University of Basel, Switzerland

Professional experience

06/2015 – today	Investment Strategist & Portfolio Manager, Private Client Bank
03/2011 – 05/2015	Analyst, Compass Capital
07/2011 – 12/2012	Private Equity Trainee, Akina (formerly Lombard Odier & Co. PE)
02/2011 – 11/2012	Junior Consultant Transaction Advisory Services, Ernst & Young
03/2009 – 05/2011	Financial Accountant, Credit Suisse